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An Integrative Approach Using Remote Sensing and Social Analysis to Identify Different Settlement Types and the Specific Living Conditions of its Inhabitants

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The Case Study of Mega City Delhi, India

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“It’s expensive to be poor.”

(Anonymous inhabitant of a slum in Delhi, India, 2006)

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Abstract

The 21st century is the century of the cities and of urbanization.

Someday in 2007, the world population reached a historical landmark: for the first time in human history, more than half of the world´s population was urban. A stagnation of this *urbanization* process is not in sight, so that by 2050, already 70 percent of humankind is projected to live in urban settlements. Over the last few decades, enormous migrations from rural hinterlands to steadily growing cities could be witnessed coming along with a dramatic growth of the world's urban population. The speed and the scale of this growth, particularly in the so called less developed regions, are posing tremendous challenges to the countries concerned as well as to the world community. Within *mega cities* the strongest trends and the most extreme dimensions of the urbanization process can be observed. Their rapid growth results in uncontrolled processes of fragmentation which is often associated with pronounced poverty, social inequality, socio-spatial and political fragmentation, environmental degradation as well as population demands that outstrip environmental service capacity. For the majority of the mega cities a tremendous increase of informal structures and processes has to be observed. Consequentially *informal settlements* are growing, which represent those characteristic municipal areas being subject to particularly high population density, dynamics as well as marginalization. They have quickly become the most visible expression of urban poverty in developing world cities.

Due to the extreme dynamics, the high complexity and huge spatial dimension of mega cities, urban administrations often only have an obsolete or not even existing data basis available to be at all informed about developments, trends and dimensions of urban growth and change. The knowledge about the living conditions of the residents is correspondingly very limited, incomplete and not up to date. Traditional methods such as statistical and regional analyses or fieldwork are no longer capable to capture such urban process. New data sources and monitoring methodologies are required in order to provide an up to date information basis as well as planning strategies to enable sustainable developments and to simplify planning processes in complex urban structures.

This research shall seize the described problem and aims to make a contribution to the requirements of monitoring fast developing mega cities. Against this background a methodology is developed to compensate the lack of socio-economic data and to deduce meaningful information on the living conditions of the inhabitants of mega cities. Neither social science methods alone nor the exclusive analysis of remote sensing data can solve the problem of the poor quality and outdated data base. Conventional social science methods cannot cope with the enormous developments and the tremendous growth as they are too labor-, as well as too time- and too cost-intensive. On the other hand, the physical discipline of remote sensing does not allow for direct conclusions on social parameters out of remote sensing images.

The prime objective of this research is therefore the development of an integrative approach – bridging remote sensing and social analysis – in order to derive useful information about the living conditions in this specific case of the mega city Delhi and its inhabitants. Hence, this work is established in the overlapping range of the research topics remote sensing, urban areas and social science.

Delhi, as India’s fast growing capital, meanwhile with almost 25 million residents the second largest city of the world, represents a prime example of a mega city. Since the second half of the 20th century, Delhi has been transformed from a modest town with mainly administrative and trade-related functions to a complex metropolis with a steep socio-economic gradient. The quality and amount of administrative and socio-economic data are poor and the knowledge about the circumstances of Delhi’s residents is correspondingly insufficient and outdated. Delhi represents therefore a perfectly suited study area for this research.

In order to gather information about the living conditions within the different settlement types a methodology was developed and conducted to analyze the urban environment of the mega city Delhi. To identify different settlement types within the urban area, regarding the complex and heterogeneous appearance of the Delhi area, a semi-automated, object-oriented classification approach, based on segmentation derived image objects, was implemented. As the complete conceptual framework of this research, the classification methodology was developed based on a smaller representative training area at first and applied to larger test sites within Delhi afterwards.

The object-oriented classification of VHR satellite imagery of the QuickBird sensor allowed for the identification of five different urban land cover classes within the municipal area of Delhi. In the focus of the image analysis is yet the identification of different settlement types and amongst these of informal settlements in particular. The results presented within this study demonstrate, that, based on density classes, the developed methodology is suitable to identify different settlement types and to detect informal settlements which are mega urban risk areas and thus potential residential zones of vulnerable population groups. The remote sensing derived land cover maps form the foundation for the integrative analysis concept and deliver therefore the general basis for the derivation of social attributes out of remote sensing data.

For this purpose settlement characteristics (e.g., area of the settlement, average building size, and number of houses) are estimated from the classified QuickBird data and used to derive spatial information about the population distribution. In a next step, the derived information is combined with in-situ information on socio-economic conditions (e.g., family size, mean water consumption per capita/family) extracted from georeferenced questionnaires conducted during two field trips in Delhi. This combined data is used to characterize a given settlement type in terms of specific population and water related variables (e.g., population density, total water consumption). With this integrative methodology a catalogue can be compiled, comprising the living conditions of Delhi’s inhabitants living in specific settlement structures – and this in a quick, large-scaled, cost effective, by random or regularly repeatable way with a relatively small required data basis.The combined application of remotely sensed imagery and socio-economic data allows for the mapping, capturing and characterizing the socio-economic structures and dynamics within the mega city of Delhi, as well as it establishes a basis for the monitoring of the mega city of Delhi or certain areas within the city respectively by remote sensing. The opportunity to capture the condition of a mega city and to monitor its development in general enables the persons in charge to identify unbeneficial trends and to intervene accordingly from an urban planning perspective and to countersteer against a non-adequate supply of the inhabitants of different urban districts, primarily of those of informal settlements.

This study is understood to be a first step to the development of methods which will help to identify and understand the different forms, actors and processes of urbanization in mega cities. It could support a more proactive and sustainable urban planning and land management – which in turn will increase the importance of urban remote sensing techniques. In this regard, the most obvious and direct beneficiaries are on the one hand the governmental agencies and urban planners and on the other hand, and which is possibly the most important goal, the inhabitants of the affected areas, whose living conditions can be monitored and improved as required. Only if the urban monitoring is quickly, inexpensively and easily available, it will be accepted and applied by the authorities, which in turn enables for the poorest to get the support they need.

All in all, the listed benefits are very convincing and corroborate the combined use of remotely sensed and socio-economic data in mega city research.

Zusammenfassung

Das 21. Jahrhundert ist das Jahrhundert der Städte und der Urbanisierung.

Im Laufe des Jahres 2007 hat die Weltbevölkerung eine historische Marke überschritten: zum ersten Mal in der Geschichte der Menschheit lebte mehr als die Hälfte der Weltbevölkerung in Städten. Ein Ende dieser Entwicklung ist bis dato nicht in Sicht, so dass bis zum Jahr 2050 bereits ein urbaner Bevölkerungsanteil von 70% prognostiziert wird. Die letzten Jahrzehnte wurden von einem dramatischen Bevölkerungswachstum dominiert, welches mit einer enormen Landflucht und stetig wachsenden Städten einherging. Die Geschwindigkeit und der Umfang des Bevölkerungswachstums, insbesondere in den Entwicklungs- und Schwellenländern, stellen nicht nur die betroffenen Länder, sondern auch die Weltgemeinschaft vor immense Herausforderungen. Die dramatischsten Tendenzen und extremsten Ausprägungen werden dabei in *Megastädten* verzeichnet. Deren rapides Wachstum führt zu unkontrollierten Entwicklungsprozessen und Fragmentierung, was meistens mit ausgeprägter Armut, sozialen Ungleichmäßigkeiten, sozial-räumlicher sowie politischer Zersplitterung und Umweltbelastungen einhergeht. Die resultierenden Erfordernisse der Bevölkerung überfordern zudem schlicht die vorhandenen Umgebungsbedingungen. In der Mehrheit der Megastädte lässt sich ein drastisches Wachstum von informellen Strukturen beobachten. In Konsequenz entstehen *informelle Siedlungen* (sog. Slums), welche sich durch eine besonders hohe Bevölkerungsdichte, besonders dynamische Prozesse sowie soziale Ausgrenzung charakterisieren. Informelle Siedlungen sind schnell zu den offensichtlichsten und dramatischsten Erscheinungsbildern urbaner Armut geworden.

Aufgrund der hohen Dynamik, der Komplexität und der enormen räumlichen Ausdehnung von Megastädten stehen den städtischen Verwaltungen oftmals nur unzureichende oder gar keine Daten zur Verfügung, um über die Tendenz und die Dimension des urbanen Wachstums und die Veränderung des urbanen Raums ausreichend informiert zu sein. Der Umfang und die Qualität der Informationen über die Lebensverhältnisse der dortigen

Bevölkerung sind demzufolge sehr limitiert, unvollständig und nicht aktuell. Traditionelle Methoden wie statistische oder regionale Analysen und Untersuchungen vor Ort sind solchen Dimensionen der Stadtentwicklung nicht mehr gewachsen. Neue Datenquellen und Beobachtungsmethoden werden benötigt, um eine aktuelle Datenbasis zu erhalten. Zudem müssen neue stadtplanerische Strategien entworfen werden, um nachhaltige Entwicklungen zu ermöglichen und Planungsprozesse in komplexen urbanen Räumen zu vereinfachen.

Diese Arbeit soll eben diese Problematik aufgreifen und einen Beitrag zur Entwicklung adequater Beobachtungsmethoden für sich schnell verändernde megaurbane Räume leisten. Zu diesem Zweck wird eine Methodik entwickelt, die den Mangel an sozio-ökonomischen Daten kompensieren und verwertbare Informationen über die Lebensbedingungen der Bewohner von Megastädten ableiten soll. Weder sozialwissenschaftliche Methoden alleine, noch der alleinige Einsatz von Fernerkundung kann das Problem der mangelhaften und veralteten Datenbasis lösen. Konventionelle sozial-wissenschaftliche Methoden können mit der enormen Entwicklungsgeschwindigkeit und dem starken Wachstum nicht Stand halten, da sie zu arbeits-, zeit- und kostenintensiv sind. Die Fernerkundung wiederum lässt in ihrer rein physikalischen Ausprägung keine direkten Rückschlüsse auf sozio-ökonomische Daten zu.

Das primäre Ziel dieser Arbeit ist daher die Entwicklung eines integrativen Ansatzes, der eine Brücke zwischen Fernerkundung und Sozialwissenschaften schlägt, um verwertbare Informationen über die Lebensbedingungen der Einwohner einer Megastadt, im vorliegenden Fall der Bewohner Delhis, ableiten zu können. Diese Dissertation bewegt sich folglich in einem disziplinübergreifenden Forschungsfeld zwischen Fernerkundung, urbanem Raum und Sozialwissenschaft.

Indiens rasant wachsende Hauptstadt Delhi, mittlerweile mit 25 Millionen Einwohnern die zweitgrößte Stadt der Welt, stellt ein Paradebeispiel für eine Megastadt dar. Seit der zweiten Hälfte des 20. Jahrhunderts hat sich Delhi von einer bescheidenen Stadt, hauptsächlich durch Handel und Verwaltungsfunktionen geprägt, zu einer komplexen Metropole mit einem starken sozialen Gefälle entwickelt. Auch hier sind die Qualität und die Verfügbarkeit von sozio-ökonomischen Daten mangelhaft und folglich auch die Informationen über die Lebensumstände der Einwohner unzureichend und veraltet. Vor diesem Hintergund stellt Delhi ein ideales Untersuchungsgebiet für diese Studie dar.

Mit dem Ziel Informationen über die Lebensbedingungen in den verschiedenen Siedlungstypen innerhalb Delhis abzuleiten, wurde eine Methodik zur Untersuchung des städtischen Raums der Metropole entwickelt und getestet. Um die Identifikation verschiedener Siedlungstypen innerhalb des Stadtgebiets zu ermöglichen, wurde ein semi-automatischer objekt-orientierter Klassifikationsansatz implementiert. Dem konzeptionellen Rahmen der Gesamtarbeit treu bleibend, wurde auch die Klassifikationsmethode zunächst auf einer kleineren repräsentativen Trainingsfläche entwickelt und anschließend auf größere Testgebiete innerhalb Delhis angewandt.

Der objekt-orientierte Klassifikationsansatz der höchstaufgelösten Satellitendaten des QuickBird-Sensors ermöglicht die Identifikation verschiedener urbaner Landbedeckungsklassen innerhalb des Stadtgebiets von Delhi. Im Fokus der Datenanalyse steht jedoch die Identifikation von verschiedenen Siedlungstypen und von informellen Siedlungen im Besonderen. Die Ergebnisse dieser Studie zeigen, dass die entwickelte Methode in der Lage ist, basierend auf Dichteklassen, verschiedene Siedlungstypen zu identifizieren und informelle Siedlungen auszuweisen, welche mega-urbane Risikogebiete und somit Wohngebiete mit potenziell gefährdeten Bewohnern darstellen. Die aus den Fernerkundungsdaten abgeleiteten Landbedeckungsklassen stellen dabei die Grundlage für den integrativen Analyseansatz dar und formen somit die grundlegende Basis für die Ableitung sozio-ökonomischer Attribute aus Fernerkundungsdaten.

Zu diesem Zweck wurden auf Basis der klassifizierten QuickBird-Daten Siedlungseigenschaften wie Siedlungsfläche, durchschnittliche Gebäudegröße und Anzahl der Häuser bestimmt und dazu verwendet, räumliche Informationen über die Bevölkerungsverteilung abzuleiten. In einem nächsten Schritt wurden die aus den Satellitenbildern abgeleiteten Informationen mit sozio-ökonomischen In-situ Informationen (z.B. Familiengröße, durchschnittlicher Wasserverbrauch pro Einwohner/Familie) kombiniert. Diese In-situ Daten stammen aus georeferenzierten Fragebögen, die während zweier Befragungen vor Ort in Delhi erhoben wurden. Die kombinierten Daten ermöglichen schließlich die Charakterisierung eines bestimmten Siedlungstyps hinsichtlich spezifischer bevölkerungs- und wasserrelevanter Parameter (z.B. Bevölkerungsdichte, Gesamtwasserverbrauch). Mit diesem integrativen Ansatz könnte ein Katalog zusammengestellt werden, der die Lebensbedingungen der Bewohner Delhi´s in den jeweiligen Siedlungsstrukturen umfasst – und zwar auf schnelle, großräumige, kosteneffektive, zufällig oder regelmäßig wiederholbare Weise mit einer relativ kleinen erforderlichen Datenbasis. Die kombinierte Anwendung von Fernerkundungs- und sozio-ökonomischen Daten ermöglicht somit die Kartierung, Erfassung und Charakterisierung der sozio-ökonomischen Strukturen und Dynamiken innerhalb der Megastadt Delhi. Des Weiteren wird mittels Fernerkundung eine Basis für das Monitoring der Megastadt Delhi oder ausgewählter Gebiete innerhalb der Stadt geschaffen. Die Möglichkeit den Zustand einer Megastadt zu erfassen und ihre generelle Entwicklung zu überwachen, befähigt die verantwortlichen Personen negative Trends frühzeitig zu erkennen und aus der Perspektive der Stadtplanung entsprechend intervenieren als auch einer nicht-adequaten Versorgung der Bewohner unterschiedlicher Stadtviertel, v.a. den Bewohnern der informellen Siedlungen, entgegensteuern zu können.

Diese Studie soll als ein erster Schritt zur Entwicklung einer Methode verstanden werden, die die Identifizierung und das Verständnis unterschiedlicher Ausprägungen, Akteure und

Prozesse von Urbanisierung in Megastädten ermöglicht. Die Stadtplanungsbehörden und das verantwortliche Management können dabei unterstützt werden, sich aktiv für eine nachhaltigere Stadtentwicklung einzusetzen, was im Erfolgsfall wiederum den Stellenwert der urbanen Fernerkundung anwachsen lassen wird. In dieser Hinsicht sind einerseits die Behörden und Stadtplaner die Nutznießer der entwickelten Methode. Andererseits profitieren aber auch, was möglicherweise eigentlich das wichtigere Ziel ist, die Bewohner der betroffenen Siedlungsgebiete selbst, deren Lebensbedingungen fortan überwacht und folglich auch positiv beeinflusst werden können. Nur wenn das städtische Monitoring schnell und kostengünstig und darüber hinaus leicht zugänglich ist, wird es von den zuständigen Behörden akzeptiert und dementsprechend auch angewendet werden. Dies wiederum ermöglicht es den Ärmsten der Gesellschaft, zumindest theoretisch, die Unterstützung zu bekommen die sie dringend benötigen.

Alles in allem sind die aufgeführten Vorteile sehr vielversprechend und untermauern das Potenzial des interdisziplinären Einsatzes von Fernerkungsdaten und sozio-ökonomischen Daten in der Megastadtforschung.

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List of Acronyms

AM	Arithmetic Mean
AS	Assumption
ASM	Angular Second Moment
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVIRIS	Airborne Visible InfraRed Imaging Spectrometer
BMBF	Bundesministerium für Bildung und Forschung (German Federal Ministry of Education and Research)
CHRIS	Compact High Resolution Imaging Spectrometer
CON	Contrast
DDA	Delhi Development Authority
DEM	Digital Elevation Model
DFG	Deutsche Forschungsgemeinschaft (German Research Foundation)
DJB	Delhi Jal Board
DN	Digital Number
ENT	Entropy
ENVISAT	Environmental Satellite
ETM	Enhanced Thematic Mapper
HUPs	Human Urban Patches
IFOV	Instantaneous Field of View
IGBP	International Geosphere-Biosphere Programme
IGU	International Geographical Union
IHDP	International Human Dimensions Programme
IHS	Intensity-Hue-Saturation
IRS	Indian Remote Sensing Satellite
IYPE	International Year of Planet Earth
JJ	Jhuggi Jhompri
GIS	Geographic Information System
GLCM	Grey-Level Co-occurrence Matrix
GSD	Ground Sampling Distance
KIA	Kappa Index of Agreement
LIDAR	Light Detection and Ranging
LUCC	Land Use/Cover Change
MERIS	Medium Resolution Imaging Spectrometer

MD	Minimum Distance
ML	Maximum Likelihood
MODIS	Moderate Resolution Imaging Spectroradiometer
MIR	Mid-InfraRed
MRS	Multi-Resolution Segmentation
MS	Multi Spectral
MSS	Multispectral Scanner System
NCT	National Capitol Territory
NDVI	Normalized Differenced Vegetation Index
NIR	Near-InfraRed
NN	Nearest Neighbor
NOAA	National Oceanic and Atmospheric Administration
OA	Overall Accuracy
OOA	Object-Oriented Analysis
PAN	Panchromatic
PCA	Principal Component Analysis
RS	Remote Sensing
RWA	Resident Welfare Association
UN	United Nations
UNEP	United Nations Environment Programme
URL	Uniform Resource Locator
USGS	U.S. Geological Survey
SEaTH	Separability and Thresholds (algorithm)
SPOT	Système Probatoire d´Observation de la Terre
TIR	Thermal InfraRed
TM	Thematical Mapper
TTA	Test and Training Area
VC	Visual Counting
VDU	Very Dense Urban
VHR	Very High Resolution
V-NIR	Visible and Near-Infrared
VIS	Visible
WHO	World Health Organization

Chapter 1

Introduction

In contrast to the last century where the majority of people used to live in rural areas, at present more than half of the world population lives in urban settlements. By 2014, already 3.9 billion people were living in cities. The total amount of urban residents may even reach 70 percent by 2050. In addition to that, the United Nations (UN) estimates that about 90 percent of the future population growth will take place in cities. Future prospects moreover predict that, as in the last few decades, the majority of this growth will be registered in the urban areas of the developing countries (KÖTTER 2004, PLANETEARTH 2005, UN-HABITAT 2003a 2006 and 2014, TURKSTRA & RAITHELHUBER 2004). The enormous dimension of the urban growth is a fundamental component of the *Global Change* and turns the urbanization into one of the crucial future key challenges of the world population. Hence, the 21st century can be called the century of the cities and of urbanization.

The urbanzitation process has resulted in fundamental changes to the environment and to the social structure. This process by itself however does not cause a problem yet. In theory, as well as in popular opinion, cities do offer positive potentials for employment, education, services and the expectation of sufficient health care. But, in fact, the chances and risks are distributed in an extremely unbalanced way. There is no other place, where the contrast between rich and poor is more striking. The chances for prosperity, development and wealth are only in reach for a minority of the urban population (HEINRICHS 2010). The urban growth is becoming more and more problematic the less successful this rapid and today mostly unplanned process can be managed in terms of structural planning, public infrastructure development and limiting the social, economic and ecologic impact of the urbanization to reasonable dimensions (KEINER & SCHMID 2003). Hence, the explosive dynamic and the dramatic dimension of the urbanization often overstrain sustainable development strategies for urban areas. This situation is being exacerbated by an almost complete lack of planning or preparation of urban growth in most parts of the world. Not least a lack of knowledge about the spatial distribution of the (population) growth impedes concrete measures and hence involves overflowing, unplanned and therefore uncontrolled local urban growth (HEINRICHS & KABISCH 2006). This development is often associated with a rapid increase in social inequality and pronounced poverty, as well as population demands, socio-spatial and political fragmentation, and environmental degradation that outstrip environmental service capacity (such as waste disposal and treatment as well as drinking water and sanitation) (PLANETEARTH 2005, Kraas 2005, UN-HABITAT 2006, UN 2003a). These severe risks of course predominantly affect the already poorest of the urban population living in the so called informal settlements.

The everlasting growth of the mega cities is maybe the most obvious indicator for a global urbanization process (HEINRICHS 2010). In this context, the strongest trends and the most extreme dimensions of the urbanization process can be observed within mega cities, with consequences on regional and global scale which can hardly be foreseen by today (HEINRICHS & KABISCH 2006). Mega cities are more than just large agglomerations. In rapidly urbanizing regions they are also foci of global risk and hot spots of demographic and socio-economic dynamics. Their rapid growth results in uncontrolled processes of fragmentation which counteracts governance and steering. In most of the mega cities that have grown to unprecedented size, the pace of urbanization has far exceeded the growth of necessary infrastructure and services. As a result, for the majority of the mega cities a tremendous increase of informal structures and processes has to be observed. Hence, an increasing number of urban dwellers are facing insufficient basic infrastructure, substandard housing, overcrowding and unhealthy living conditions (KRAFFT ET AL. 2003, TURKSTRA & RAITHELHUBER 2004). Recent research has shown that almost one billion people, or 32 percent of the world’s urban population, are living in informal settlements, the majority of them in the developing world. The locus of global poverty is moving to the cities, a process now recognized as the “urbanization of poverty” (UN-HABITAT 2003b). Hence, the identification, observation and analysis of such “hot spots” of urban challenges is of special importance in planning strategy (PLANETEARTH 2005).

Urban decision makers are confronted with a challenging environment. “To be able to conduct a policy aimed towards sustainable regional development, they require up to date information, supplied by efficient data-extraction systems that support their decision making process” (VAN DE VOORDE 2004). Due to the extreme dynamics, the high complexity and huge spatial dimension of mega cities, urban administrations often only have an obsolete or not even existing data basis available to be at all informed about developments, trends and dimensions of urban growth and change. Against this background, traditional methods such as statistical and regional analyses or fieldwork are limited to capture the urban process. New data sources and monitoring methodologies as well as planning strategies are required in order to provide an up to date information basis and thus to enable sustainable developments and to simplify planning processes in complex urban structures (KÖTTER 2004). In this regard, remote sensing represents an area-wide und up to date alternative to conventional data acquisition methods. Using satellite-based earth observation technique it is possible to derive urban related information with a high spatial and temporal resolution. Especially very high resolution (VHR) satellites (such as QuickBird, IKONOS or World View-1) can significantly support the detection and surveillance of urban development and do implicitly contain a rich source of useful information for urban managers and planners (VAN DE VOORDE 2004).

The relevance of the application of remotely sensed image data within urban areas with the aim to examine socio-economic questions needs to be particularized though. There are great differences between urban areas in more developed and less developed countries in the potential, applicability and need of remote sensing data and the capacity for integration of remote sensing with socio-economic data (MILLER & SMALL 2003). In the majority of cases there are almost no or only incomplete datasets available in the less developed countries. Particularly mega cities in less developed countries like Dhaka, Jakarta, Lagos or Delhi are data poor environments. In agglomerations like these, hardly any or no profound knowledge about development and growth of the city is available. Temporal resolution, spatial coverage and quality of administrative and socio-economic data are insufficient and the knowledge about the living conditions of the residents is correspondingly very limited, incomplete and not up to date. In contrast to this, the data basis in the more developed countries is much better. Mega cities like Tokyo or New York are data rich environments. In the (mega) cities of Europe (e.g., London) or other more developed regions, the living conditions of its residents are more or less well known and due to the comparably high living standard, a surveillance and examination appears not really to be required.

Delhi, as India’s fast growing capital, with an estimated number of inhabitants of almost 25 million in 2014, where a decrease of the population growth is even after 60 years of a continuous increase in population not expected in the near future, represents a prime example for a mega city (BRONGER 2004, UN 2014). Since the second half of the 20th century, Delhi has been transformed from a modest town with mainly administrative and trade-related functions to a complex metropolis with a steep socio-economic gradient (KRAFFT 2001). As described above in general, politicians and planners here are as well hardly or not at all equipped with profound knowledge about development and growth of their city. The quality and amount of administrative and socio-economic data are poor and the knowledge about the living conditions of Delhi's residents is correspondingly insufficient and out-dated. With Delhi's present situation, the extreme and obviously visible contrast between different settlements within the urban area and the corresponding highly diverging living conditions of their residents, Delhi appears to be a well suitable test site for this research objective.

This work is established in the overlapping range of the research topics remote sensing, urban areas and social science. Already this set-up shows a paradigm shift within the science from isolated research tasks of single disciplines to an interdisciplinary and integrated approach. This interdisciplinarity represents one of the central aspects of this study itself and of the research initiative which this work is embedded in.

In the following, the specific research objectives, the corresponding research questions, as well as the working hypotheses, which will be addressed in this study, are presented.

1.1 Research Objectives

Resuming the above explanations, it can be concluded that due to the high dynamic within the mega cities of today's world, their development cannot be captured and monitored quickly and precisely enough any more with conventional methods. In order to make a controlled planning process within these complex urban structures possible, new observation instruments and methods are required, which are capable to deliver relevant and up to date information. This requires the consideration of appropriate earth observation data together with the development of new methods and procedures for its analysis and interpretation.

While the specific aim of this thesis is the development of a method to derive socio-economic information from remotely sensed data in a mega urban area, there is of course a greater context. With an integrative approach, embedding as well social science as the physical discipline of remote sensing, a method shall be developed, that allows for supplying the persons in charge with important and up to date data of the development and conditions of mega urban areas within their responsibility. This in turn shall put the decision makers into a position being able to step into action to help the poorest and most heavily affected of today's civilization changes.

In order to implement this interdisciplinary approach, first of all one very basic question needs to be answered. How can these two disciplines – remote sensing and social science – be combined and which is the linking element that can be used? In other words, where is the link between the individual living conditions of the inhabitants within the mega city and remote sensing (images) – where is the link between people and pixels?

The field of investigation of social scientists regarding urban areas comprises basically socio-economic variables such as health care, birthrate, water supply or disposal, educational background etc. (cf. Figure 1-1). These variables, which decisively characterize and influence the life and the living conditions of the inhabitants, are not directly visible from outside. From the perspective of social science, the idea of this study is that the individual living conditions of the inhabitants are reflected in the structure of their settlement within the mega city. This means that attributes as for example building size and density, quality of the road network or the fraction of vegetation are in a certain way related to the living standard of the inhabitants.

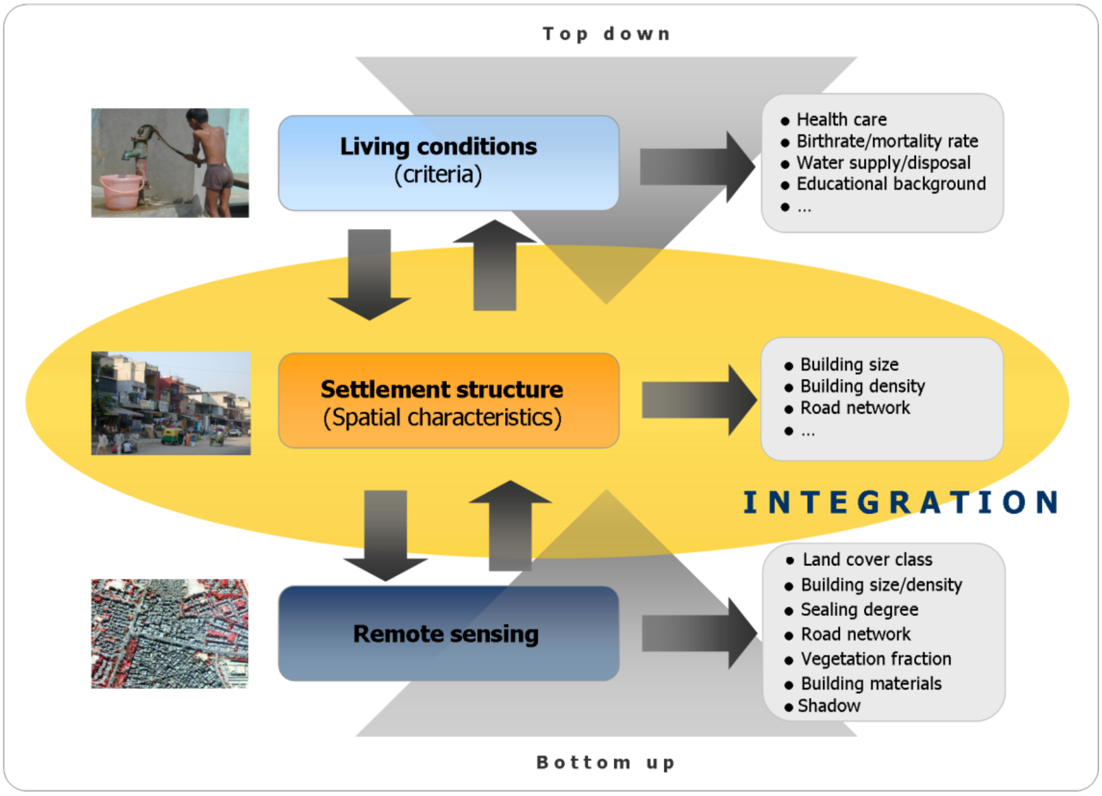

Figure 1-1: Conceptual framework of the research.

From the perspective of physical science, on the other hand, remote sensing can provide data for various visible attributes associated with human activity in urban areas — first and foremost the environmental impacts of diverse social, demographic or economical processes. Surveillance and monitoring of land cover for example can visualize the fingermarks of urbanization. Moreover, remote sensing images can provide a number of further indicators which can be linked with social science studies. For example spatial parameters such as building size, building density and materials as well as sealing degree or vegetation fraction can be detected and monitored (cf. Figure 1.1). All these spatial characteristics are part of the settlement structure or respectively define in their specific combination a certain settlement type. This specific settlement type in turn, can as a whole be visualized by remote sensing.

Considering the described coherences, the settlement structure appears to be the missing link between remote sensing and social science regarding urban areas. Therefore it is postulated in this study, that *it is possible to derive information about the living conditions of the people by analyzing remote sensing images of their urban living environment.*

Based on the explanations above the reasearch presented in this dissertation aims to examine the following working hypotheses:

- **The living conditions of the residents are reflected in the settlement structure of mega cities.**
- **The settlement structures of mega cities are reflected in remote sensing images.**
- **Remote sensing provides the opportunity to detect, observe and assess complex spatial patterns of urban structures.**
- **The settlement structure acts as an interface between remote sensing and social science in mega city research.**
- **It is possible by means of remote sensing data (and by including socio-economic data) to reveal information about the living conditions of urban dwellers.**
- **Remote sensing has the potential to be used as "social measuring instrument".**

To verify the correctness of the hypotheses established above and to corroborate the validity of the approach, the primary research questions, which have to be answered within this study therefore, are:

- **How are the inhabitants of the mega cities?**
- **How are the living conditions of the residents?**
- **Do the living conditions visibly affect the settlement structures within mega cities?**
- **Is it possible to identify settlements within a mega city by analyzing remote sensing data where the living conditions are particularly poor and where therefore is direct need for action?**

- **Is remote sensing able to be a "social measuring instrument"?**

Out of the context of the investigations additional questions arise that are examined and discussed within this thesis as well:

- **How can remote sensing improve the current spatial and socio-economic data basis of mega cities?**
- **How big is the potential of remote sensing in the field of mega city research? What is possible?**
- **Where are the limitations of the use of remote sensing data to respond to socio-economic questions in mega urban areas?**
- **What can remote sensing do for social science and especially for urban studies?**
- **And what can social science do for urban remote sensing?**

1.2 Thesis Outline

Based on the research questions and hypotheses mentioned above, the basic facts, concepts, methods, results and evaluations are structured in this research as follows:

Chapter 2 covers the general issue of the global urbanization process. It is the aim to give an overview over the past developments as well as the specific current processes, phenomena, impacts and challenges of urbanization. The focus here is put on the one hand on the structural threats, which arise out of a too dynamic and uncontrolled urbanization process. On the other hand, this chapter is describing the direct social effects on the inhabitants and thus on their living conditions. Mega cities are the most extreme phenomena of the world-wide urbanization process and are therefore hot spots of demographic and socio-economic dynamics.

An introduction into the current status of research in the field of remote sensing of urban areas is given in chapter 3. The key attributes of the urban environment are identified, and the capability of remote sensing technologies to measure these attributes is specified. In this context, the wide field of application of remote sensing data in urban environments is outlined. In the following, the technical enhancements of remote sensing sensors and their characteristics are described together with the methodological developments and the resulting impacts on urban remote sensing. The chapter illustrates moreover the possibility of integrating social science and remote sensing, which is a key intention of the approach developed within this study. An interim conclusion is closing this chapter and forms a basis for the objectives and investigations presented in this work.

The study area of this research, the mega city of Delhi, India, is introduced in chapter 4. Starting with general background information on the urban development, the population growth and the resulting implications, this chapter explains the selection of suitable test sites within the urban area of Delhi.

A summary of all the data used in the present work is provided in chapter 5. This includes on the one hand the remote sensing data processed and analyzed. But also the required pre-processing of the satellite data is explained here. On the other hand this chapter introduces the primary data of the household survey conducted in-situ in the mega city of Delhi. The execution of the sampling is subjected to a short review and is discussed critically. During the field campaign additional information was gathered through personal observation techniques, mapping and ground truthing. The corresponding data base generated is described at the end of this chapter.

Chapter 6 presents an overview of the study workflow and the conceptual framework of the thesis (cf. Figure 6-1). It is postulated within this study, that the settlement structure can be considered as the central link between remote sensing and social science in the urban environment. Hence, starting with the segmentation of the image data and the object-oriented classification of land cover, this chapter is describing the classification methodology to identify different settlement types within the research environment in general and of informal settlements in particular. The developed classification approach is implemented into the Software eCognition™ (BAATZ ET AL. 2004) and is designed on the one hand to achieve a high precision and on the other hand to allow for an easy transferability of the (semi-) automated method to other test sites within Delhi. Within this chapter moreover, an integrative method to analyze urban areas is developed, which is used to investigate whether VHR remote sensing data can provide settlement characteristics in order to derive in combination with socio-economic data information on the living conditions of the urban residents. Hence one of the key questions of this thesis is examined, whether remote sensing can be a social measuring tool.

In chapter 7, the results of the object-based image data analysis are presented. This includes both, the outcome of the segmentation process as well as the deliverables of the object-oriented classification approach. The classification results represent the information basis for the determination of urban settlement structures within the complex urban area of the mega city of Delhi. At the same time the results of the image data analysis form the basis for the derivation of physical settlement parameters presented in chapter 8. Hence, the quality of the land cover classification is already of decisive importance for the following investigation of the urban environment of Delhi. The section involves therefore a quality assessment of the classification results. The chapter closes with a summary and a critical survey of the classification results.

The integrative use of remote sensing derived information and socio-economic data is in the focus of chapter 8**.** Based on the classification results of the satellite imagery (chapter 7.2) the different identified settlement types of Delhi, in combination with the questionnaire data, are characterized and the specific living conditions are evaluated. The investigations of this chapter aim to deliver answers to the key questions raised in the introduction and the additional potentials of the developed integrative analysis in comparison to the conventional methods are elaborated. For this purpose the results of the integrative analysis are being summarized and evaluated, and are beheld in a greater context, as well as the benefits of this method are presented. Critical aspects are identified and collected, and are as well included in the examination and appraisal of the developed integrative analysis method. The chapter is subdivided into the presentation of the results, a validation part as well as a summary and appraisal of the combined use of remotely sensed imagery and socio-economic data.

In chapter 9 a conclusion summarizes the most important results of the study. The fundamental working hypotheses postulated in the beginning of the study are recapitulated and their validity is discussed. The potentials of remote sensing for the developed (integrative) approach in particular as well as for the mapping, capturing and characterizing of the socio-economic structures and dynamics within a mega city like Delhi in general are appraised. An outlook on the perspectives of urban remote sensing research and the linking of remote sensing and social science to be investigated in the future is closing this thesis.

Chapter 2

Urbanization and Mega Cities: The Challenge of the 21st Century

> "The growth of cities will be the single influence on development in the 21st century."
>
> (Opening words of the UNFPA's 1996 State of World Population Report)

Over the last five decades, the world experienced a dramatic growth of its urban population. The speed and the scale of this growth, particularly in the so called *less developed* regions, are continuing to pose tremendous challenges to the countries concerned as well as to the world community. "Monitoring these developments and creating sustainable urban environments remain crucial issues on the international development agenda" (UN 2004).

Urbanization

1. Increase in the proportion of a population living in urban areas;
2. Process by which a large number of people becomes permanently concentrated in relatively small areas, forming cities

(Source: The definition has been quoted word by word from UN 1997)

Especially, mega cities are subject to various dynamics of *Global Change* — understood as global environmental change as well as global socio-economic and political change (Goudie 2005, Johnston et al. 2002). At the same time, mega cities vice versa affect the Global Change by their immense development dynamic. Thus, the dynamics and complexity of the processes observed in mega cities as well as their global economic, social, and spatial effects form one of the greatest current challenges (Kraas & Nitschke 2006, Kraas 2007c). The *United Nations*

Environment Programme (UNEP) noted that "managing the urban environment sustainability will become […] one of the major challenges for the future" (UNEP 2002).

Against this background, the following chapter shall give an overview over the past developments as well as the specific current processes, phenomena and problems of the urbanization.

2.1 Urbanization and Global Change: Current Trends

Urbanization as a social phenomenon and the physical transformation of landscapes is currently one of the most dramatic global changes. Its speed, scale and global connectedness turn the urban habitat, particularly in mega cities and large agglomerations, into both a space of risk and a space of opportunity (PLANETEARTH 2005).

Between 2007 and 2050, the world´s total population is expected by the UN to increase by 2.5 billion; passing from 6.7 billion to 9.2 billion (UN 2008b & UN-HABITAT 2013) (cf. Figure 2-1). At the same time, the population living in urban areas is projected to gain 3.1 billion, passing from 3.3 billion in 2007 to 6.4 billion in 2050 (cf. Figure 2-2 and Table 2-1). This means that the world´s urban population continues to grow faster than the total population of the world.

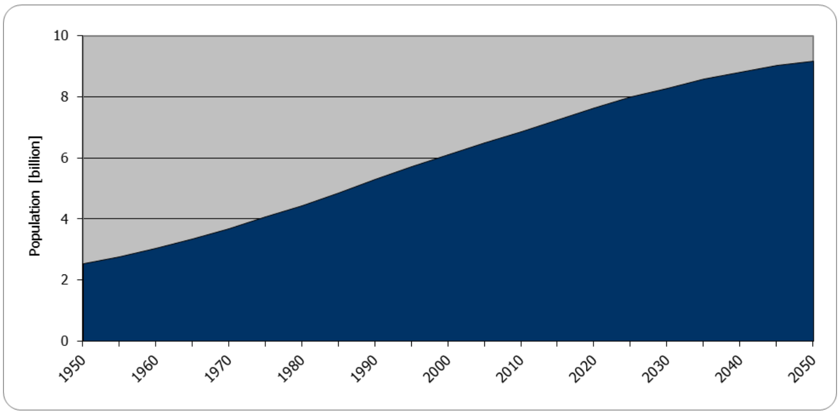

Figure 2-1: Global population growth: 1950 – 2050 (Data sources: UN World Population Prospects: The 2006 Revision, UN World Urbanization Prospects: The 2007 Revision and UN- HABITAT Global Report on Human Settlements 2013).

In 1950, only 30 percent of the world´s population resided in urban settlements. Someday in 2007, the world population reached a historical landmark: for the first time in history the urban population has equalled the rural population of the world and, from then on, the world will be inhabitated by more urban dwellers than rural ones. By 2030 already 60 percent and by 2050 even 70 percent of humankind is projected to be urban (Figure 2-2 and Table 2-1). The United Nations (UN) estimates that about 90 percent of future population growth will take place in cities[1] (PLANETEARTH 2005, TURKSTRA & RAITHELHUBER 2004, KÖTTER 2004, UN 2004 & 2008a, UN-HABITAT 2013).

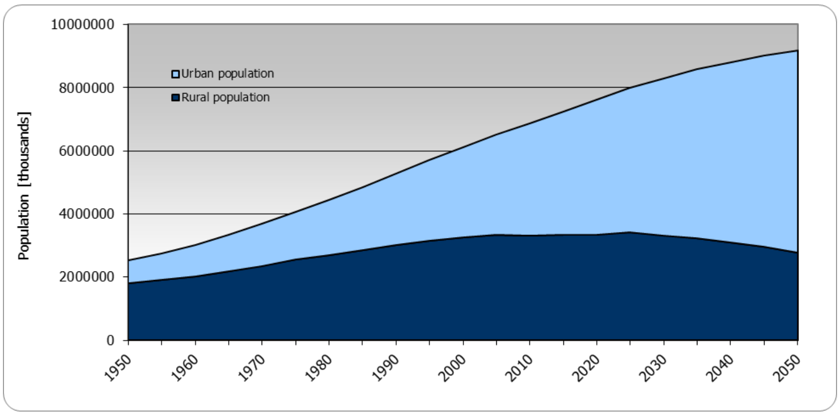

Figure 2-2: Urban and rural populations of the world: 1950 – 2050 (Data sources: UN World Population Prospects: The 2006 Revision, UN World Urbanization Prospects: The 2007 Revision and UN- HABITAT Global Report on Human Settlements 2013).

Table 2-1: Total, urban and rural populations by development group, selected periods: 1950 – 2050

	Population [billions]							Proportion urban [%]		Average annual rate of change
Development group	1950	1975	2000	2003	2014	2030	2050	2014	2050	2000 - 2030
Total population										
World...............................	2.52	4.07	6.07	6.30	7.24	8.13	9.55	54	66	0.97
More developed regions......	0.81	1.05	1.19	1.20	1.26	1.24	1.30	78	85	0.13
Less developed regions......	1.71	3.02	4.88	5.10	5.98	6.89	8.25	48	63	1.15
Urban population										
World...............................	0.73	1.52	2.86	3.04	3.88	4.94	6.34			1.83
More developed regions......	0.43	0.70	0.88	0.90	0.98	1.01	1.13			0.47
Less developed regions......	0.31	0.81	1.97	2.15	2.9	3.93	5.23			2.29
Rural population										
World...............................	1.79	2.55	3.21	3.26	3.36	3.19	3.21			-0.03
More developed regions......	0.39	0.34	0.31	0.31	0.28	0.23	0.19			-1.05
Less developed regions......	1.40	2.21	2.90	2.95	3.09	2.96	3.02			0.06

Data source: UN - World Urbanization Prospects: The 2003 & 2014 Revision

The urbanization levels of different regions of the world are highly divergent. “The transformative power of urbanization was felt earlier in today´s more developed regions and they have reached high levels of urbanization” (UN 2008a). In the more developed regions, in 2007, already 74 percent of the inhabitants lived in cities, whereas in the less developed regions only 44 percent of the inhabitants were urban (UN 2008a). Nevertheless, the high global urbanization rate is foremost a consequence of rapid urbanization in the last decades and especially in the world´s less developed regions (cf. Figure 2-3 and Table 2-1). Also in the future the majority of the world´s total population growth between 2000 and 2030 is

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[1] While in 1950 only 746 million people lived in urban areas, the urban population reached one billion in 1960, two billion in 1985, and crossed the three billion mark in 2002. It is projected to attain 4 billion in 2017 and 5 billion in 2030. (UN2004).

expected to be absorbed by the urban areas of the less developed regions. Already by 2017, the number of urban dwellers will equal the number of rural dwellers in the less developed regions (cf. Figure 2-3) (TURKSTRA & RAITHELHUBER 2004, KÖTTER 2004, UN 2004, 2008b & 2014, UN-HABITAT 2003a and 2006). "Migration from rural to urban areas and the transformation of rural settlements into urban places are important determinants of the high urban population growth anticipated in the less developed regions" (UN 2004). By 2050, the proportion of urban dwellers in the more developed regions will have increased to 86 percent and to 67 percent in the less developed regions. All in all, the world population is expected to be 70 percent urban in 2050 (UN 2008a, UN 2014).

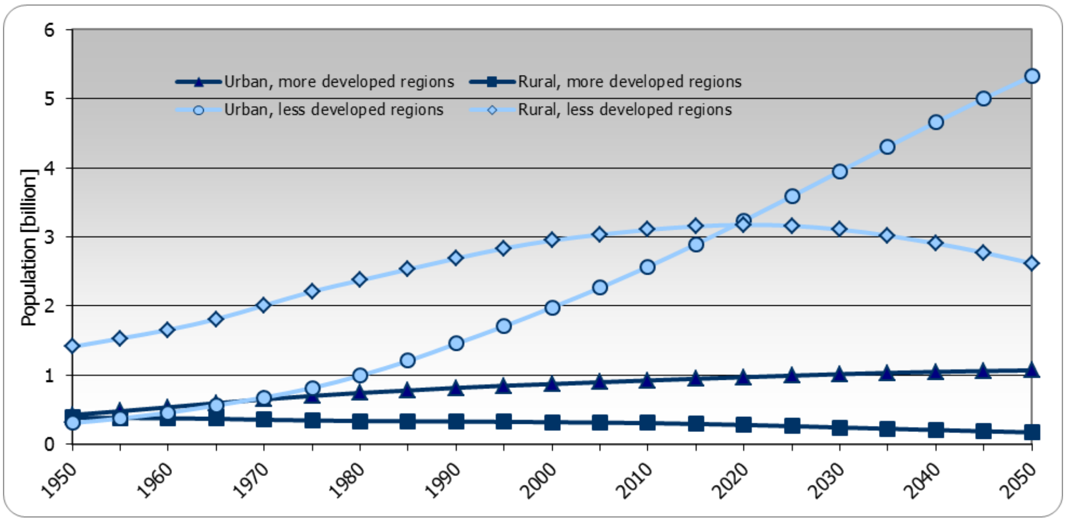

Figure 2-3: Urban and rural population in more and less developed regions: 1950 – 2050. Almost all of the world's total population growth between 2000 and 2030 is expected to be absorbed by the urban areas of the less developed regions. By 2017, the number of urban dwellers will equal the number of rural dwellers in the less developed regions. *(Data sources: UN World Population Prospects: The 2006 Revision and UN World Urbanization Prospects: The 2007 Revision).*

Urban population growth is not only a phenomenon of the less developed regions; it is a phenomenon concentrated in Asia and Africa in particular. By 2030, Asia and Africa will each have more urban inhabitants than any other major area, with Asia alone accounting for more than half of the urban population of the world. Asia and Africa are urbanizing faster than any other region of the world and are projected to become 56 and 64 percent urban by 2050. Just three countries – namely India, China and Nigeria – together are expected to account for 37 percent of the projected growth of the world´s urban population between 2014 and 2050. Solely India is projected to add 404 million urban dwellers within this time frame (UN 2004, 2008a, and 2014).

As mentioned above, the urban areas of the world are expected to absorb all the population growth expected over the next decades. Since, at the same time, a considerable amount of people living in rural areas actually will migrate into the cities, the world´s rural population is expected to reach its peak just in a few years. The rural population is anticipated to decline slightly from 3.3 billion in 2003 to 3.2 billion in 2030 (cf. Figure 2-4). Africa and Asia are today home to nearly 90 percent of the world´s rural population (UN 2004 & 2008a).

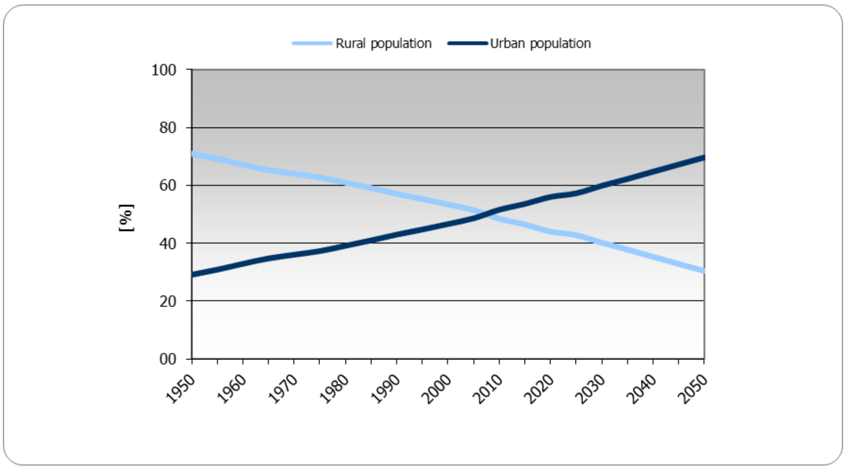

Figure 2-4: Urban and rural population of the world: 1950 – 2050. In 1950, urban-dwellers represented only 29 percent of the global population. The urban proportion grew to 49 percent in 2005 (3.2 billion people). Current projections indicate that the 50 percent mark was crossed in 2007 *(Data sources: UN World Population Prospects: The 2006 Revision and UN World Urbanization Prospects: The 2007 Revision, UN Urban Population, Development and the Environment 2007 and UN- HABITAT Global Report on Human Settlements 2013)*.

There is great diversity in the characteristics of the world´s urban environments. To this effect, today´s 3.9 billion urban dwellers (UN 2013) are distributed unevenly among urban settlements of different size. In discussing urbanization, the focus often is on large cities, cities whose populations are larger than those of many countries (UN 2008a). In 2007, 19 urban agglomerations were listed as mega cities with a population of at least 10 million inhabitants. "Despite their visibility and dynamism, mega cities account for a small though increasing proportion of the world urban population: nearly 9 percent in 2007 and nearly 10 percent in 2025" (UN 2008a). In contrast to this, at the same time, close to half of the world´s urban population live and will continue to live in relatively small settlements of less than 500,000 inhabitants (UN 2008a). Whereas several decades ago most of the world´s largest urban agglomerations were found in the more developing regions, today´s large cities are concentrated in the global South, and the fastest-growing agglomerations are medium-sized cities with 500,000 to 1 million inhabitants located in Asia and Africa.

Since the investigations of this case study are concentrated on the mega city Delhi and its inhabitants, the prevalent thesis puts its focus as well on one of the largest cities of the world. In the following chapter the phenomenon "mega city" will be described in detail.

2.2 Mega Cities – Definitions and Dimensions

The term "mega city" generally describes the greatest category of urban agglomerations, whereas several definitions are pointed out in the literature. In quantitative terms, mega cities are defined to be metropolises with a population of 10 million and more (e.g., UN 2004, MERTINS 1992), more than 8 million (e.g., FUCHS ET AL. 1994, CHEN & HELIGMAN 1994, UN 1987) or more than 5 million inhabitants (e.g., BRONGER 1996 & 2004, FELDBAUER & PARNREITER 1997). Moreover, some authors define a minimum population density (> 2,000 inhabitants/km²) and only include cities with a single dominant centre (BRONGER 1996). Thus, polycentric agglomerations, such as the Rhine-Ruhr area in Germany, for example, with 12.8 million inhabitants, are excluded whereas in other statistics this polycentric mega-urban area is included (e.g., UN 2002, 2004). KRAAS (2007b, c) found that, for present purposes, using the population threshold of 5 million inhabitants has the advantage of including the "emerging mega cities", especially in the global South and transitional economies. Many of these agglomerations are growing extremely fast and will become the mega cities of tomorrow. In conclusion any such setting of thresholds for mega cities is necessarily subjective and thus open to debate (BRONGER 1994, KRAAS 2007b, c). Furthermore, there is the difficulty of the reliability of up to date population figures given due to inconsistent censuses, estimations and projections, as well as of inconsistent spatial demarcations for administrative regions. All of these criteria are affecting the reliability and are hampering international statistical comparability of urban agglomerations (BRONGER 1996, KRAAS 2007b). Against these considerations, some authors ask for a more qualitative perception as well as a more comprehensive understanding of mega cities as in fact functional mega-urban regions (e.g., KRAAS 2007b, c).

Large urban agglomerations are not solely a phenomenon of the modern age. There have already been very large cities, in relation to the territorial total population, in the antiquity and in the Middle Ages (e.g., Babylon in Mesopotamia). But in the narrow sense mega cities have only started to develop with the industrialization in the 19th century (KRÖHNERT 2003). In 1801, London (with 1.1 million inhabitants) has raised up to the first metropolis and world city of the modern age at the same time (BRONGER 2004). Around 1900 London (6.5 million, cf. Table 2-2) was still the largest city of the world. While in the 1950s there were only six (mega) cities (Tokyo, New York, London, Shanghai, Paris and Moscow), four of six in industrialized countries, with a population greater than 5 million (BRONGER 2004), by 1975 this number rose to already 21 and even to 42 in 2000 (UN 2004) (cf. Table 2-2). In the 20th century the mega cities of the industrialized countries, with the exception of Tokyo, were characterized only by minor population growth. In London, for example, the population decreases since 1940 (KRÖHNERT 2003 and BRONGER 2004).

Table 2-2: The most populated cities in the world (1900 – 2000)

	1900*			1950*			1975**		2000**	
Position	Urban agglomeration	Reference area [km²]	Population [1,000]	Urban agglomeration	Reference area [km²]	Population [1,000]	Urban agglomeration	Population [1,000]	Urban agglomeration	Population [1,000]
1	London	1,579	6,510	Tokyo	13,138	13,051	Tokyo	26,615	Tokyo	34,450
2	Tokyo	13,138	5,248	New York	10,768	12,736	New York[2]	15,880	Mexico City	18,006
3	New York	10,768	4,936	London	1,579	8,197	Shanghai	11,443	New York[2]	17,846
4	Paris	2,576	4,187	Shanghai	1,598	6,824	Mexico City	10,690	São Paulo	17,099
5	Berlin	889	2,712	Paris	2,576	6,684	Osaka-Kobe	9,844	Mumbai[1]	16,086
6	Osaka-Kobe	2,850	2,025	Moscow	879	5,100	São Paulo	9,614	Calcutta	13,058
7	Chicago	4,926	1,897	Osaka-Kobe	2,850	4,982	Buenos Aires	9,143	Shanghai	12,887
8	Vienna	415	1,662	Buenos Aires	3,880	4,727	Los Angeles	8,926	Buenos Aires	12,583
9	Calcutta	897	1,488	Chicago	4,926	4,714	Paris	8,630	Delhi	12,441
10	St. Petersburg	570	1,439	Calcutta	897	4,589	Beijing	8,545	Los Angeles	11,814
11	Philadelphia	...	1,418	Los Angeles	12,561	4,368	Calcutta	7,888	Osaka-Kobe	11,165
12	Mumbai[1]	4,355	1,260	Mumbai[1]	4,355	3,800	Moscow	7,623	Jakarta	11,018
13	Manchester	1,287	1,255	Berlin	889	3,707	Rio de Janeiro	7,557	Rio de Janeiro	10,839
14	Birmingham	899	1,248	Philadelphia	...	3,548	London	7,546	Beijing	10,803
15	Moscow	879	1,120	Mexico City	4,607	3,348	Mumbai[1]	7,347	Cairo	10,398

[1] Bombay, [2] New York-Newark area

Data sources: *BRONGER 2004, **UN - World Urbanization Prospects: The 2003 Revision

In contrast to this, the population growth has proceeded much more dynamically in the cities located in the so called *Third World*. Since the end of World War II mega cities have developed almost exclusively in less developed regions (cf. Table 2-3 and Table 2-4) (KRÖHNERT 2003, UN 2004). Currently, most of the world's mega cities are located in developing countries (UN 2004, 2014) (cf. Figure 2-5). COY & KRAAS (2003) speak even about more than two-thirds of the mega cities which are located in developing countries, most of them in East and South Asia.

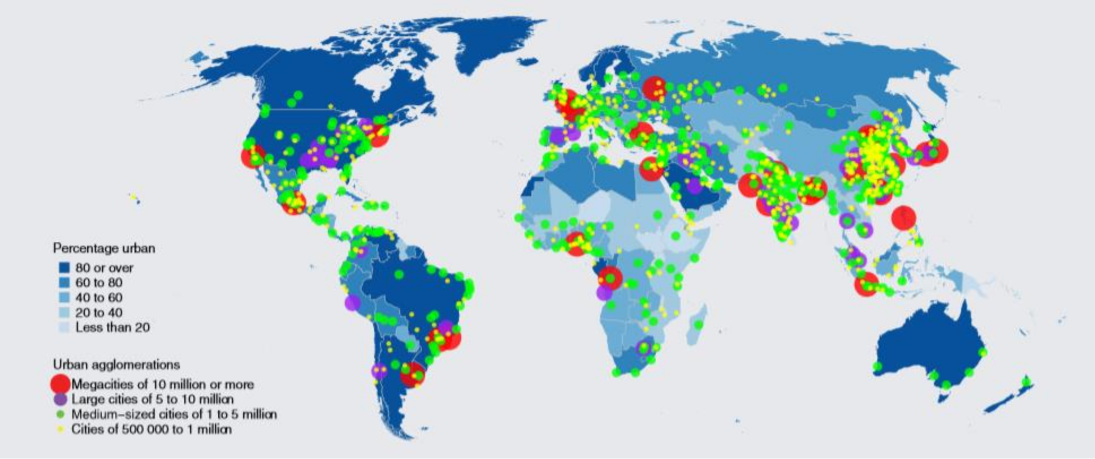

Figure 2-5: Percentage urban and location of urban agglomerations with at least 500,000 inhabitants in 2014 *(Source: UNITED NATIONS, World Urbanization Prospects: The 2014 Revision)* (For a time series illustrating the world´s urbanization process between 1970 and 2030 please see A.1 in the Appendix).

In 2003, 33 (of the 46) (mega) cities with 5 million inhabitants or more were in less developed countries, and by 2015, 45 (out of such 61) cities are expected to be from the more less developed regions (UN 2004). In some mega cities the population figures have increased dramatically over the last decades of the 20th century (1975 – 2000). Representative examples are: Mexico City (10.7 – 18.1 million), Jakarta (4.8 – 11.0 million), Karachi (4.0 – 10.0 million), Istanbul (3.6 – 8.7 million), Mumbai (Bombay) (7.3 – 16.1 million) or the city of Delhi (4.4 – 12.4 million). In Lagos (1.9 – 8.7 million) and Dhaka (2.2 –

10.6 million) the population amount has even quintupled within the same period (UN 2004) (cf. Table 2-2 and Table 2-4).

Table 2-3: Urbanization in the 20th century

	> 5 Mio.			> 10 Mio.			Total		
Year	IC	DC	Σ	IC	DC	Σ	IC	DC	Σ
1900	3	–	3	–	–	–	3	–	3
1920	4	–	4	–	–	–	4	–	4
1940	2	–	2	2	–	2	4	–	4
1950	4	2	6	2	–	2	6	1	7
1960	6	5	11	2	–	2	8	5	13
1970	6	10	16	2	–	2	8	10	18
1980	6	13	19	3	4	7	9	17	26
1990	7	16	23	4	9	13	11	25	36

IC: Industrialized Countries, DC: Developing Countries
Data source: BRONGER 1996

The highest growth rates, with over five percent annual increase in population,were recorded in the mega cities of the developing countries during the fifties and sixties of the last century. Although the population of these cities increases further, the rate of growth declines slowly since that time. For the future for almost all of these agglomerations a further decline of the growth rates is predicted (KRÖHNERT 2003, UN 2004).

According to the "World Urbanization Prospects" of the UN (2004) the number of (mega) cities with 5 million inhabitants or more is projected to increase from 46 in 2003 to 61 in 2015 worldwide (cf. Figure 2-5). Hence, approximately 600 million people will be living in these megalopolises. Among these, the number of urban agglomerations with 10 million inhabitants or more is projected to increase from 19 in 2007 to 41 in 2030 (UN 2004, UN 2008a).

With 35million inhabitants in 2003, Tokyo is by far the most populous urban agglomeration in the world. The second largest agglomeration is Mexico City, followed by New York, São Paulo and Mumbai (Bombay). In 2030, Tokyo is projected to remain the world´s largest urban agglomeration with 37 million inhabitants, followed by Delhi where the population grew extremely fast and has reached 25 million inhabitants already in 2014 and is projected to rise on swiftly to 36 million in 2030 (cf. Table 2-4) (UN 2004 & 2014).

In qualitative terms, mega cities are characterized by — in principle with differences between such in more developed and developed regions — intensive processes of expansion, suburbanization and concentration, functional primacy, infrastructural, social, economical and ecological overload the development of polarized and fragmented societies as well as the increasing loss of control and governance at growing informality. The next paragraph will go into more detail of the qualitative features of mega cities as well as the effects and impacts of the urbanization process.

Table 2-4: Urban agglomerations with 10 million inhabitants or more in 2000, 2003, 2014 and 2030

	2000		2003		2014		2030	
Position	Urban agglomeration	Population [millions]	Urban agglomeration	Population [millions]	Urban agglomeration	Population [millions]	Urban agglomeration	Population [millions]
1	Tokyo, Japan	34.4	Tokyo	35.0	Tokyo	37.8	Tokyo	37.2
2	Mexico City, Mexico	18.1	Mexiko City	18.7	Delhi	25.0	Delhi	36.0
3	New York, USA[1]	17.8	New York[1]	18.3	Shanghai	23.0	Shanghai	30.8
4	São Paulo, Brazilia	17.1	São Paulo	17.9	Mexiko City	20.8	Mumbai	27.8
5	Mumbai, India	16.1	Mumbai	17.4	São Paulo	20.8	Beijing	27.7
6	Calcutta, India	13.1	Delhi	14.1	Mumbai	20.7	Dhaka	27.4
7	Shanghai, China	12.9	Calcutta	13.8	Osaka	20.1	Karachi	24.8
8	Buenos Aires, Argentina	12.6	Buenos Aires	13.0	Beijing	19.5	Cairo	24.5
9	Delhi, India	12.4	Shanghai	12.8	New York[1]	18.6	Lagos	24.2
10	Los Angeles, USA[2]	11.8	Jakarta	12.3	Cairo	18.4	Mexiko City	23.9
11	Osaka-Kobe, Japan	11.2	Los Angeles[2]	12.0	Dhaka	17.0	São Paulo	23.4
12	Jakarta, Indonesia	11.0	Dhaka	11.6	Karachi	16.1	Kinshasa	20.0
13	Rio de Janeiro, Brazilia	10.8	Osaka-Kobe	11.2	Buenos Aires	15.0	Osaka	19.9
14	Beijing, China	10.8	Rio de Janeiro	11.2	Calcutta	14.8	New York[1]	19.9
15	Cairo, Egypt	10.4	Karachi	11.1	Istanbul	14.0	Calcutta	19.1
16	Dhaka, Bangladesh	10.2	Beijing	10.8	Chongqing	12.9	Guangzhou, Guar	17.8
17	Moscow, Russian Federation	10.1	Cairo	10.8	Rio de Janeiro	12.8	Chongqing	17.4
18	Karachi, Pakistan	10.0	Moscow	10.5	Manila	12.8	Buenos Aires	17.0
19	Metro Manila, Philippines	10.0	Metro Manila	10.4	Lagos	12.6	Manila	16.8
20	Lagos, Nigeria	8.7	Lagos	10.1	Los Angeles[2]	12.3	Istanbul	16.7

[1] Refers to the New York - Newark urbanized area.

[2] Refers to the Los Angeles - Long Beach - Santa Ana urbanized area.

Data source: UN - World Urbanization Prospects: The 2003 & 2014 Revision

2.3 Effects, Impacts and Challenges of Urbanization and Mega Cities

The present worldwide trend toward urbanization is intimately connected with economic development and leads to profound changes in social organization, land use, and patterns of human behavior (BETTENCOURT ET AL. 2007, CRANE & KINZING 2005). Central feature of these changes is an unprecedented demographic scale, which will lead to important, but yet poorly understood impacts on the global environment. Consequently, a major challenge worldwide is to understand and predict how changes resulting from urbanization will impact the interactions between the global environment and the human being (UN 2004 and BETTENCOURT ET AL. 2007).

FUCHS ET AL. (1994) emphasize that, "while it is true that mega city development is rooted in its specific country or regional context […] mega cities have more in common with each other than with their own hinterlands". Nevertheless, all things considered, clear differences in for instance infrastructure quality, social polarization, the level of economic development and transformation or governability and political leadership have to be recognized and should not be neglected (PLANETEARTH 2005 and KRAAS 2003, 2005 and 2007b).

In a superficial view, mega cities are mainly associated with numerous disadvantages. Often, they are solely perceived as sources of diverse problems as well as originators, promoters and victims of risks. But they possess likewise several characteristics which can be beneficial for a positive development (KRAAS 2007b). Thus, the increasing concentration of people in mega cities presents both opportunities and challenges. Hence, a more balanced perception is needed in order to point out both sides of the coin.

In theory, as well as in popular opinion, mega cities are the incubators of huge growth and innovation. They are the focal points of globalization, engines of the economy as well as the driving force for development. Mega cities harbor a wide spectrum of human potential and skill, creativity and cultural diversity. Moreover, they provide opportunities for education, employment, and services as well as an expectation of better health care. Agglomerations of this category offer positive potential for global transformation, e.g. minimization of "space consumption", high effectiveness of resources applied as well as efficient disaster prevention (BETTENCOURT ET AL. 2007, KÖTTER 2004, KRAAS 2005, MOORE ET AL. 2003 and PLANETEARTH 2005).

In fact, mega cities are also foci of global risk. They are increasingly vulnerable systems because their rapid and mostly unplanned urban growth is often associated with pronounced poverty, social inequality, socio-spatial and political fragmentation (sometimes with extreme forms of segregation, disparities and conflicts), environmental degradation and population demands that outstrip environmental service capacity (HARDOY ET AL. 2001, MOORE ET AL. 2003, PLANETEARTH 2005, UN-HABITAT 2006). Mega cities do not only face risks in consequence of external events, whether natural or man-made, they likewise contain, produce and reinforce hazards (cf. Figure 2-6). Thus, mega cities, affected by the global environmental, socio-economic as well as political changes to which they contribute, are both producers and victims of risk at the same time (PLANETEARTH 2005, MITCHELL 1999a und 1999b, KRAAS 2007c, TRICE 2006).

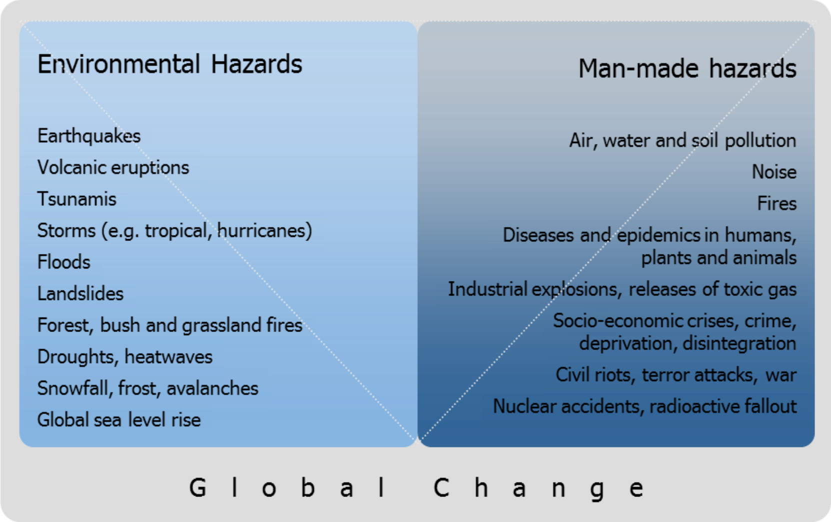

Figure 2-6: Environmental and man-made hazards — impacts of Global Change *(Sources: KRAAS 2003 and MITCHELL 1999b, modified).*

In order to illustrate both sides of the coin, Table 2-5 outlines the problems, risks and disadvantages as well as the benefits, chances and advantages accompanying the (mega-) urbanization process. This compilation does not make a claim to be complete, but rather shall give an impression about the complexity of the possible impacts.

Table 2-5: Juxtaposition of the impacts of (mega-) urbanization

	Problems, risks and disadvantages	**Benefits, chances and advantages**
Ecological dimension	▪ Urban expansion, sprawl and fragmented land use pattern ▪ Pollution of air, water and soil, sewage water problems (insufficient land use planning) ▪ Waste disposal: uncollected, illegal and toxic waste ▪ Expansion in ecologically fragile areas (riversides, coasts, slopes etc.) arising serious consequences: environmental degradation, flooding or land subsidence ▪ Sealing and degradation of fertile soil ▪ Environmental health problems	▪ Decreased space consumption (per head) partly through high-rise construction ▪ Optimised land use patterns, efficient land use planning ▪ More efficient use of ressources (water, food, energy etc.) ▪ Sustainable urban agricultural and green space policy ▪ Comprehensive monitoring and management of nature-human interactions
Economic dimension	▪ Insufficient or nonexistent infrastructure (water, energy, transport, communication) ▪ Un- and under-employment ("oversupply of labor") ▪ Low labor wages and exploitation of labor force ▪ Wide spectrum of informal (uncontrolled, party illegal) activities ▪ Unaccounted for water and energy flows ▪ Tremendous migration and commuter flows	▪ Improvement of infrastructure (water, energy, transport, communication) ▪ Increasing income and wealth ▪ Increasing interaction of all economic sectors ▪ Growth of productivity ▪ Scientific and technological innovations, growth of creativity ▪ Improved welfare systems ▪ Less vulnerability, growing resilience and robustness ▪ Human security for all
Social dimension	▪ Loss of social coherence ▪ Reinforcement and spread of socio-economic disparities and social fragmentation ▪ Decline of access to health system, education and security infrastructure ▪ Informal, partly illegal settlements ▪ Growing vulnerabiliy in marginalized population groups ▪ Social injustice, misuse of social power ▪ Corruption, bribery, conflicts, crime, …	▪ Growth of community and neighborhood coherence ▪ Growth of cultural diversity, interaction and exchange ▪ Improved education and health care systems ▪ Rising life expectancy ▪ Multi-disaster prepardness ▪ Growth of social justice ▪ Development and strengthening of independent control mechanisms against corruprtion, burbery etc. ▪ Enhancement of social laws (e.g. housing, labor)
Political dimension	▪ Loss of governability and steering capabilities ▪ Growing informality in decision making processes, self-organization of pubic functions, … ▪ Loss of representation of general public (e.g. migrants, minorities) ▪ Incoherent government laws, regulations, rules	▪ Growth of width, depth and availability of information and communication; international connectivity ▪ Growth of participation in political decision making processes ▪ Development and strengthening of civil society institutions ▪ Improvement of governance processes, political coherence and enforcement of laws and regulations

Sources: KRAAS 2007b, KRAAS & NITSCHKE 2006, KÖTTER 2004

Against this background and with regard to the global socio-economic change, the mega cities of the world have to be differentiated in "rich" and "poor" (SCHOLZ 2002). Depending on which impacts are predominant, the mega cities can be assigned to the respective category. "Rich" mega cities are located in developed and transition countries. As examples have to be named for instance Bangalore, Bangkok, Tokyo, Beijing, Shanghai, Los Angeles or New York. They are global functional control centers with high-ranking global services as well as corporate headquarters which produce for the regional and national, but also for the global market. Hence, they profit from the earnings of the international division of labor and involvement in global socio-economic and political networks. These mega cities can be put on a level with the term "global city", which have a global cultural, political or economic relevance. Thus, many control and command functions of the world system are also located in the richest mega cities (KRAAS 2007c, KRÖHNERT 2003). However, "poor" mega cities, as e.g., Dhaka, Lagos or Karachi, can rather completely be assigned to the developing countries. Primarily they are the "collecting ponds" for rural migration, with large percentages of the population living below the poverty line. In these cities, the production and service levels of a wide range of informal activities persist only at regional and national scale. Consequently, the mega cities of the developing world play no major role, despite their enormous total populations, within the global urban system. It is not becoming apparent either at the moment that the mega cities of the developing countries will be able to cope better with their economic "peripheral location" and their social problems within the next years (KRAAS 2007b and KRÖHNERT 2003).

Until recently, rural settlements were the epicenter of poverty and human suffering. Poverty, however, is today increasing more rapidly in urban than in rural areas but has still received far less attention. On this account, the attention in the further course shall be put on the development, effects and impacts of this process. Since the assessment of the living conditions is in the main focus of this thesis and the same have to be judged as insufficient particularly in informal settlements, this topic will be taken up repeatedly in the further course of this study. The following section 2.4 will give a description of the increasing growth or the spreading of informal settlements as well as the corresponding implications.

2.4 The Urbanization of Poverty

"Slum, semi-slum, and superslum…to this has come the evolution of cities."

(quoted by Patrick Geddes in MUMFORD 1961)

According to the UN (2005) an outstanding characteristic of urban population growth in the 21st century is that it will be composed, to a large extent, of poor people. As a consequence, the locus of global poverty is moving to the cities, a process now recognized as the "urbanization of poverty" (UN-HABITAT 2003b).

In most of the mega cities that have grown to unprecedented size, the pace of urbanization has far exceeded the growth of necessary infrastructure and services. As a consequence, for the majority of the mega cities a tremendous increase of informal structures and processes has to be observed (TURKSTRA & RAITHELHUBER 2004). Thus, an increasing number of urban dwellers are faced with overcrowding, an insufficient basic infrastructure and unhealthy living conditions (KRAFFT ET AL. 2003). The resulting poverty in combination with a lack of affordable housing are the driving forces behind the formation of informal settlements, which offer solely substandard living conditions to their inhabitants (cf. Figure 2-7) (TURKSTRA & RAITHELHUBER 2004).

Figure 2-7: Different types of informal housing in Delhi, India (*Photographs: S. Smollich, October 2005).*

Recent research has shown that in 2010 almost 830 million people, or about 24 percent of the world's urban population were living in informal settlements (cf. Figure 2-8), the majority of them in the developing world (cf. Figure 2-9 and Figure 2-10). If the development continues as it is today, the world´s slum population will likely increase by 6 million annually to reach nearly 900 million by 2020. This figure could easily reach one billion by 2030 unless urgent actions are undertaken to improve the living conditions of existing slum dwellers and to prevent the formation of new informal settlements (UN-HABITAT 2003b and 2012).

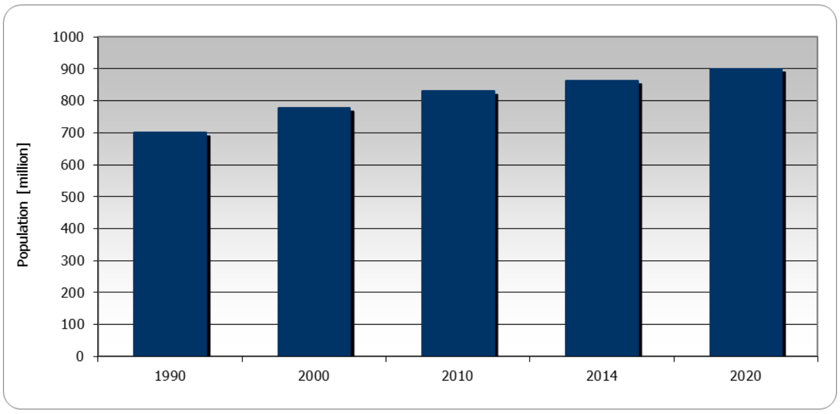

Figure 2-8: World's urban slum population between 1990 and 2020. *(Data sources: IEEE Spectrum 2007, UN-HABITAT 2003b and UN-HABITAT 2012).*

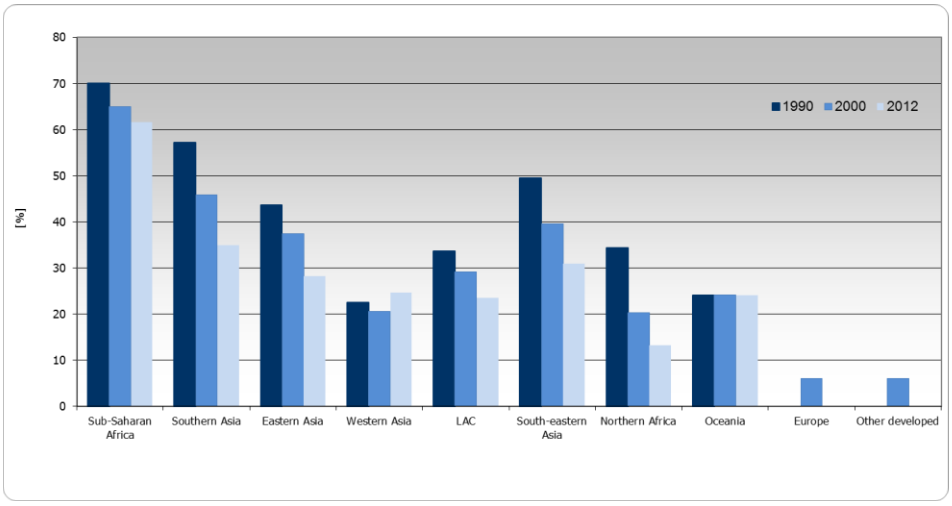

Figure 2-9: Slum dwellers as a percentage of urban population by region between 1990 and 2012 *(Data source: UN-HABITAT Global Report on Human Settlements 2003 and UN-HABITAT State of the World´s Cities 2012/2013).*

Informal settlement dwellers of the new millennium are no longer a few thousand in a few cities of a rapidly industrializing continent. They include one out of every three city dwellers, a sixth of the world's population (UNFPA 2007, UN-HABITAT 2003a). This figure will increase unless persons in charge and development agencies (amongst others) scale up their efforts to improve the living conditions of current and future urban dwellers. Until today, urban poverty as a topic receives relatively little attention from policy, authorities and agencies. However, the recent development shows that this issue attracts public interest and therefore, comes more and more into the focus (TURKSTRA & RAITHELHUBER 2004).

Informal settlements represent those characteristic municipal areas which are subject to particularly high dynamics, population density as well as marginalization. They have quickly become the most visible expression of urban poverty in developing world cities. The quality of dwellings in such settlements varies from the simplest shack to permanent structures, while access to water, electricity, sanitation and other basic services and infrastructure is usually limited. Nowadays, a variety of equivalent terms for this distinctive type of residential area exists, e.g. *slum*, *squatter settlement*, *low-income community* or *shanty town*. Up to the present, there is no internationally accepted definition and all mentioned terms are used interchangeably by agencies and authorities. The coverage of settlement types is even more complex if the variety of equivalent words in other languages and different geographical regions, e.g. *favela* (Brazil), *bustee* (India), *mabanda* (Tanzania), *township* (South Africa) or *jhuggi jhompri* (India), is considered. Consequently, the problem with measuring informal settlements starts with the lack of an agreed definition. Therefore, a first step to identify informal settlements and to quantify the population itself is to develop an operational definition of the term.

According to UN (officially adopted at a meeting in 2002) *informal settlements* are typically addressed as contiguous settlements where the inhabitants are characterized as having inadequate housing and basic services. Often they are not recognized and addressed by the public authorities as an integral or equal part of the city (UN-HABITAT 2003a). This is one of the reasons why the data base of informal settlements and their dwellers is mostly insufficient. Moreover, " [...] it is an area which combines to various extents the following characteristics:

- Insecure residential status,
- Inadequate access to safe water,
- Inadequate access to sanitation and other infrastructure,
- Poor structural quality of housing, and
- Overcrowding" (UN-HABITAT 2003a).

Other similar definitions are provided in many policy documents, for instance the Cities Alliance Action Plan (CITIES ALLIANCE 1999).

Furthermore, it is important to note, that not all poor people live in slums, and not all people who live in areas defined as slums are poor. However, to simplify matters, this study equates the urban poor with slum dwellers and the term "informal settlement" and "slum" will be used interchangeably and together in this context.

Currently over 90 percent of slum dwellers are in the developing world, whereas South Asia records the largest fraction, followed by Eastern Asia, (Sub-Saharan) Africa and Latin America (cf. Figure 2-10). Therefore, Asia dominates the global picture, having about 60 percent of the total world's slum dwellers in 2001 (UN-HABITAT 2003a and UNFPA 2007). According to the UN-HABITAT Report (2003b) (cf. Figure 2-11), the world's highest percentage of slum dwellers are in Ethiopia (an astonishing 99.4 percent of the urban population), followed by Chad (also 99.4 percent), and Afghanistan (98.5 percent).

India (with ca. 158 millions) and China (with ca. 194 millions) together even hold 37 percent of the world's slum inhabitants (cf. Figure 2-11). In Sub-Saharan Africa, "urbanization has become virtually synonymous with slum growth" (UNFPA 2007). Figure 2-9 shows that in this part of the world in 2012 nearly 62 percent of the urban population lives under slum conditions, compared to 35 percent in South-central Asia. Mumbai, with 10 to 12 million slum and pavement dwellers, is the global capital of slum dwelling, followed by Mexico City and Dhaka (9 to 10 million each), and then Lagos, Cairo, Kinshasa-Brazzaville, São Paulo, Shanghai and Delhi (6 to 8 million each) (DAVIS 2006).

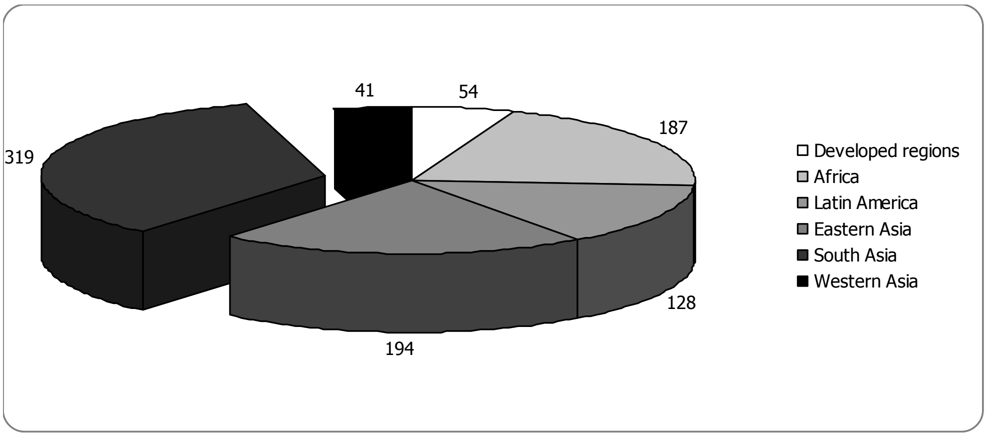

Figure 2-10: World distribution of slum dwellers [millions] by region in 2001 *(Data source: UN-HABITAT Global Report on Human Settlements 2003).*

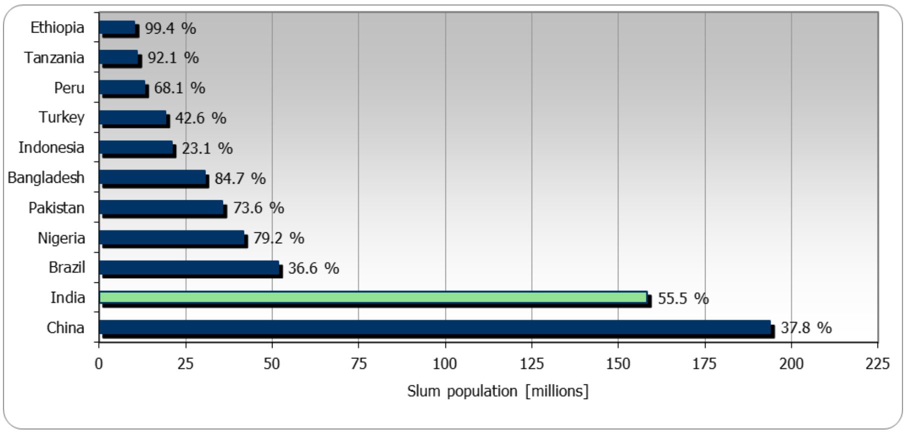

Figure 2-11: Number of slum dwellers by country and the corresponding percentage of slum dwellers of the urban population *(Data sources: UN-HABITAT Slums of the World 2003 and DAVIS 2006)*[2].

A key question of this research is, whether different settlements and informal settlements in particular can be identified from remote sensing data. Since the potential of remote sensing is restricted to the detection and analysis of "visible" characteristics of the urban environment, the outward appearance (physical entity) is important to identify settlement structures. In this regard an informal settlement is defined to be an area that combines, to various extents, the following physical characteristics:

- High building density,
- Small building size,
- Complex shape appearance to the outside, high heterogeneity within the settlement,

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[2] The data inquiry in slums is generally difficult and the published statistics hence often need to be doubted. Most assessments actually underestimate the scale and depth of urban poverty (UNFPA 2007).

- Irregular patterns,
- Substandard housing and inadequate building structures (e.g., different poor and non permanent building materials),
- Heterogeneity in the height of the buildings (mostly 1-2 levels),
- Lack of green space,
- Lack of proper structures (e.g., irregular and narrow street patterns in a bad condition),
- Hazardous locations (geologically hazardous zones as e.g., flood areas, housing on or close to garbage mountains, proximity to high-industrial pollution areas, housing around unprotected high-risk zones like railroads or airports) (SLIUZAS & KUFFER 2008, UN-HABITAT 2003a).

Principally, these physical entities of informal settlements, resulting from the social circumstances the inhabitants live in, can be detected from remote sensing data. Hence, depending on the sensor's spatial and spectral resolution, it may be possible to classify and distinguish these settlement areas from other land use or settlement forms (HOFMANN 2001a).

According to the above mentioned definition of informal settlements and what is visible in VHR satellite data, an interpretation key was developed to detect informal settlements, which uses particularly parameters like small building size, high building density, a complex shape as well as irregular and narrow street pattern. It is assumed that the detection of one or several of these attributes in the image data can be an indicator for locating an informal settlement. For details regarding the identification of informal settlements please see chapter 6 and the following.

Chapter 3

Remote Sensing of Urban Areas: Status of Research

It will be necessary to learn from recent experience and to develop new ideas and approaches to address a wide range of concerns in order to move towards sustainable urbanization. In this context, remote sensing plays a crucial role. In general there is an increased interest today in making scientific progress through using remotely sensed data in social science, which makes urban remote sensing a steadily growing field of research (TURKSTRA & RAITHELHUBER 2004, RINDFUSS & STERN 1998). Up to date and accurate urban land cover information is needed in a variety of applications, as e.g. urban planning and management. One of the challenges in the field of remote sensing in this context is to provide the persons in charge with appropriate, up to date, city wide information in a very timely manner (NIEBERGALL ET AL. 2007, UN-HABITAT 2004). New methodologies and tools, as well as techniques and policies are required to monitor urban growth and alteration across the mega city and to forecast areas of risk — all within shorter timeframes and larger scale than previously accepted (MC LAREN ET AL. 2005, HEROLD ET AL. 2003). This will support a more proactive and sustainable urban planning and land management (UN-HABITAT 2004). As long as one is depending on traditional surveying tools, e.g. interview statistics, especially in large mega cities like Delhi, the provision of such data is both, a time consuming and expensive task. This has led to the attempt to analyze remotely sensed data with the aim to extract information on urban land cover and dynamics (DARWISH ET AL. 2003).

This chapter identifies key attributes of the urban environment and specifies the capability of remote sensing technology to measure these attributes. Moreover, it summarizes the wide field of application of remote sensing data in urban environment (cf.

chapter 3.1). Chapter 3.2 focuses on the technical and methodological development and its impacts on urban remote sensing. Main emphasis lies hereby on the one hand on the further development of remote sensing sensors and their characteristics (cf. chapter 3.2.1), and on the other hand on the enhancements of remote sensing methodologies (cf. chapter 3.2.2). Chapter 3.3 illustrates the integration of social science and remote sensing as a promising agenda in urban research applications. Especially this chapter and the interim conclusion in chapter 3.4 form a basis for the objectives and investigations presented in this study.

3.1 Remote Sensing of Urban Attributes

> "Sensing cities remotely is difficult — very difficult!"
>
> (MESEV 2003)

The difference between settlement structures and the natural environment is human being and the corresponding manner and dimension of human activity which becomes evident everyday and everywhere. People create settlements that are highly spatially dynamic. It is also people who make settlements a complex phenomenon which is very difficult to capture. However, it is important to be also aware, that it is people as well who make urban settlements important enough to move into the focus of remote sensing scientists. The consequences of human activity are apparent everywhere, but they are nowhere more visible and quantifiable than in mega cities in terms of arrangements of urban physical patterns.

A major challenge in the investigation and the remote sensing of urban areas is the heterogeneity of the urban environment in terms of its spatial and spectral properties. The urban landscape is typically characterized by a heterogeneous spatial assemblage of very different units of land cover types (HEROLD 2004). It is built up with various materials such as concrete, asphalt, plastic, shingles, brick and wood. The environment is also partly covered with water bodies, different vegetation cover categories (e.g., agricultural land, parks or gardens) or bare soil areas and is composed of residential and commercial buildings, public space, transportation networks as well as utility lines in order to provide the inhabitants with the essentials and to improve as much as possible the quality of life (COWEN & JENSEN 1998, MESEV 2003 after DAUREAU ET AL. 1989, LIVERMAN ET AL. 1998, DONNAY 1999, HEROLD 2004). Hence, "there is no explicit spectral urban signal" (HEROLD 2004), which can be recorded by the remote sensor.

Airborne remote sensing instruments as well as satellites provide an opportunity to observe urban phenomena and to measure attributes of urban environments (COWEN & JENSEN 1998). Remotely sensed data, together with data available from ground-based observations, can be used for instance to detect and monitor changes in the urban environment in space and time, to develop and validate dynamic models of urban development, to capture and characterize land cover as well as land use patterns[3], and to forecast sub- and intra-urban changes in a significant number of urban attributes (cf. Table 3-1). After COWEN & JENSEN (1998) remote sensing data are thus potentially valuable both to social scientists and to urban planners and other persons in charge.

There are potentially many important components of an urban settlement that needed to be measured and monitored over time, but only the physical or respectively visible outcomes of human activity, in opposition to the direct consequences of behavior, can be detected. It is only through the analysis of the spatial configuration of physical structures using remotely sensed data that enables us to understand the human behavior becoming apparent in such spatial patterns (MESEV 2003 after GEOGHEGAN ET AL. 1998). Thus, the argument becomes cyclical — knowledge of the physical structure and shape of cities "contributes to an understanding of socio-economic functioning and knowledge of socio-economic characteristics dictates urban layout" (MESEV 2003 after MARTIN & BRACKEN 1993, MASSER 2001).

In this way, using remotely sensed data allows us to measure, with some degree of accuracy, the entity and arrangement of urban structures (land cover). It is difficult and considerably complex though to determine how these structures are being used by their residents and occupants (land use) unless specific, additional information of socio-economic and housing attributes from other sources is employed (MESEV 2003).

Sensors, air- or spaceborne, and depending on the sensor type, "take a picture" of the physical built-up environment, and receive the electromagnetic spectrum that is reflected or emitted by the surface objects to describe its properties (HEROLD 2004, JENSEN 1996, MESEV 2003). A remote sensor "sees" a plane layout of features, mostly rooftops or treetops that may or may not cover lower features such as roads, lawns, open spaces or water bodies (MESEV 2003 after FORSTER 1985, JI & JENSEN 1999). Moreover, a remotely sensed image creates a freeze-frame of the spatio-temporal urban patterns and acquires therefore the characteristics of many urban phenomena (HEROLD ET AL. 2006). The data or information received may be both qualitative and quantitative (COWEN & JENSEN 1998).

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[3] At this point it is important to specify the difference between "land cover" and "land use". The term "land cover" names the physical composition of fractions of land, i.e., tracts covered with vegetation (grass, trees), impervious tracts (concrete, asphalt) as well as shadowed and open spaces (bare soil etc.). "Land use" is the term for the anthropogenic construct of mixtures of land cover, i.e., residential areas and buildings, commercial areas and buildings, gardens and parks, or even agricultural tracts (CAMPBELL 2002, MESEV 2003, WYATT ET AL. 1993). While "land cover" can be classified directly from remote sensing data, this is not possible with "land use". Rather it is possible to derive land use from land cover classifications, although this generally requires additional data (e.g., socio-economic data) (APLIN 2003).

Some of the major urban attributes which are of great importance to understand the urban environment are summarized inTable 3-1. To detect, observe and monitor the different parameters of the urban environment, it is mandatory to be well grounded in the temporal and spatial resolutions required. Compare Table 3-2 for an overview of the different sensor systems and their spatial resolutions.

Table 3-1: Interlinkage between selected urban attributes and the remote sensing resolution required to provide corresponding information

Urban Attributes*	**Minimum Resolution Requirements**		
	Temporal	**Spatial**	**Spectral**
Land Use / Land Cover			
L1 - USGS Level 1**	5 - 10 years	20 - 100 m	V-NIR-MIR-Radar
L2 - USGS Level 2***	5 - 10 years	5 - 20 m	V-NIR-MIR-Radar
L3 - USGS Level 3***	3 - 5 years	1 - 5 m	V-NIR-MIR-Pan
L4 - USGS Level 4****	1 - 3 years	0.3 - 1 m	Pan
Building and Property Line Infrastructure			
B1 - Building perimeter, area, volume, height	1 - 2 years	0.3 - 0.5 m	Pan
B2 - cadastral mapping (property lines)	1 - 6 months	0.3 - 0.5 m	Pan
Transportation Infrastructure			
T1 - general road centerline	1 - 5 years	1 - 30 m	Pan
T2 - precise road width	1 - 2 years	0.3 - 0.5 m	Pan
…			
Utility Infrastructure			
U1 - general utility line mapping and routing	1 - 5 years	1 - 30 m	Pan
…			
Digital Elevation Model (DEM) Creation			
D1 - large scale DEM	5 - 10 years	0.3 - 0.5 m	Pan
D2 - large sclae slope map	5 - 10 years	0.3 - 0.5 m	Pan
Socio-economic Characteristics			
S1 - local population estimation	5 - 7 years	0.3 - 5 m	Pan
S2 - regional/national population estimation	5 - 15 years	5 - 20 m	V-NIR
S3 - quality of life indicators	5 - 10 years	0.3 - 30 m	Pan-NIR
Energy Demand and Conservation			
E1 - energy demand and production potential	1 - 5 years	0.3 - 1 m	Pan-NIR
E2 - building insulation surveys	1 - 5 years	1 - 5 m	TIR
Meteorological Data			
M1 - daily weather prediction	30 min - 12 hr	1 - 8 km	V-NIR-TIR
M2 - current teperature	30 min - 1 hr	1 - 8 km	TIR
M3 - current precipitation	10 - 30 min	4 km	Doppler Radar
M4 - immediate severe storm warning	5 - 10 min	4 km	Doppler Radar
M5 - monitoring urban heat island effect	12 - 24 hr	5 - 10 m	TIR
Critical Environmental Area			
C1 - stable sensitive environments	1 - 2 years	1 - 10 m	V-NIR-MIR
C2 - dynamic sensitive environments	1 - 6 months	0.3 - 2 m	V-NIR-MIR-TIR
Disaster Emergency Response			
DE1 - pre-emergency imagery	1 - 5 years	1 - 5 m	V-NIR
DE2 - post emergency imagery	12 hr - 2 days	0.3 - 2 m	Pan-NIR-Radar
DE3 - damaged housing stock	1 - 2 days	0.3 - 1 m	Pan-NIR
DE4 - damaged transportation	1 - 2 days	0.3 - 1 m	Pan-NIR
DE5 - damaged utilities	1 - 2 days	0.3 - 1 m	Pan-NIR

* This land use / land cover classification system was developed by USGS for use with remote sensing data. Its categories are appropriate for information interpreted from aerial images, and it has a hierarchical structure that lends itself tu use with images of differing scales and resolutions (ANDERSON ET AL. 1976, CAMPBELL 2002).

** Level I is tailored for use with broad-scale, low-resolution images (e.g. Landsat MSS, TM, SPOT) (ANDERSON ET AL. 1976).

*** Level II and III are composed of more detailed classes that can be interpreted from large-scale, high-medium-resolution images (e.g. SPOT pan, Landsat 7 pan, IRS pan) (CAMPBELL 2002).

**** Level IV classes may best be monitored using very high-spatial-resolution sensors (e.g. QuickBird, IKONOS), including aerial photography (COWEN & JENSEN 1998).

Data sources: COWEN & JENSEN (1998) after e.g., ANDERSON ET AL. (1976), BRANCH (1971), FORD (1979) & HAACK ET AL. (1997)

Remote sensing techniques have already shown their value in mapping urban areas (e.g., DARWISH ET AL. 2003, GUINDON ET AL. 2004, MARCHESI ET AL. 2006, TATEM ET AL. 2005, TAUBENBÖCK & ROTH 2007), and as data sources for the analysis of the urban environment (e.g., HAACK ET AL. 1997, JENSEN 1983, MESEV 2003, NETZBAND ET AL. 2010, WENG & QUATTROCHI 2006, WENG 2012). The beginning in all applications using remotely sensed data is to specify the object, surface or phenomena of interest. After MESEV (2003), "in the urban case, this is twice as difficult" than in rural or natural environments. As mentioned above, urban areas are composed of physical materials — the land cover definition. By contrast, the land use definition is defined by the specific combination of the materials to supply the urban population. Since remote sensing is a process of physical detection the direct analysis of urban land cover is a lot more straightforward than the analysis of land use (DOBSON 1993, MESEV 2003, WEBSTER 1995), and many remote sensing scientists have concentrated on this subject before.

Remote sensing data and research results have for example been applied to the detection and mapping of impervious surface areas and therefore of urban settlements of different spatial dimension (e.g., LU & WENG 2008, GAMBA & DELL'ACQUA 2008, KAMPOURAKI ET AL. 2006, YUAN & BAUER 2006, ZHANG & MAXWELL 2008, WENG 2012). Recently, mapping and particularly monitoring the percentage of sealed areas in urban environments has become of great interest as a major indicator of environmental quality and sustainable land use (KAMPOURAKI ET AL. 2006, YUAN & BAUER 2006). Impervious surfaces, including for instance residential and industrial buildings, roads, sidewalks, and parking lots, are areas where water cannot infiltrate. Hence, the amount, duration and intensity of urban storm water runoff and the transport of non-point source pollutants as well as water abundance and water quality is directly affected (DOUGHERTY ET AL. 2004, MELESSE & WANG 2008, WENG 2008). The spatial extent and occurrence of sealed surfaces may even affect urban climate by changing sensible and latent heat fluxes within the urban "atmosphere" and boundary layers (WENG 2008, YANG ET AL. 2003).

Thus, for example, the urban heat island phenomenon results from the replacement of natural landscapes with impervious surfaces and is linked to adverse economic and environmental impacts (GLUCH ET AL. 2006). The fraction of impervious cover is widely a well-accepted indicator of urbanization and urban sprawl (HOFFHINE WILSON ET AL. 2003). Urban sprawl and particularly uncontrolled sprawl occurring in large cities of developing countries requires intensive and accurate extraction and mapping of various urban features and infrastructure properties (NOBREGA ET AL. 2006). Remotely sensed data have already been used in this field of application (e.g., GRUEN 2008, HAVERKAMP 2002, HEROLD 2008, MARANGOZ ET AL. 2004, NEGRI ET AL. 2006, PÉTERI & RANCHIN 2008, SHAN & SAMPATH 2007, STILLA ET AL. 2008, SUGUMARAN, GERJEVIC & VOSS 2008, ZHANG ET AL. 2006, ZHOU & KELMELIS 2007, BHASKARAN ET AL. 2010, RAHMAN ET AL. 2010, BHATTA 2010). Especially very high-resolution (VHR) sensors are well suited to extract buildings and roads (MARANGOZ ET AL. 2004) (cf. chapter 3.2). Remotely sensed impervious surface has also been used more and more often in population estimation purposes (LIANG ET AL. 2008, XIAN 2007, AZAR ET AL. 2010) (cf. also chapter 3.3). Consequently, accurate measurements and mapping of impervious surfaces are valuable not only for environmental management activities, for example, water quality assessment, but also provide beneficial input to urban planning, for example, building infrastructure, planned development and sustainable urban growth (SCHUELER 1994).

Some of the most promising and already successfully used applications of remote sensing techniques on urban environment include "measurement of physical quantities related to environmental conditions" (MILLER & SMALL 2003). For example, using remotely sensed data researchers are able to provide broad data of reflectance and surface temperature in cities. These observations offer valuable constraints on the physical properties that are strong determinants of environmental conditions in the urban environment. This synoptic information, which is almost impossible to obtain any other way than from remote sensing data, may improve the understanding of urban climate as well as the urban heat island (UHI) effect and their direct impact to more than half of the world's population. The urban thermal microclimate affects urban mortality and morbidity as well as the quality of life and has become an important contributor for global warming (CHEN ET AL. 2006, MILLER & SMALL 2003, SMALL 2006). Already in seventies of the last century, RAO (1972) and CARLSON ET AL. (1977) have demonstrated that urban areas could be identified through the use of thermal infrared satellite data. Past studies showed that there has been an increased interest in studies of urban land surface temperatures and urban energy budget characteristics using the technology of thermal remote sensing (BALLING & BRAZELL 1988, ROTH ET AL. (1989), STREUTKER (2002), KIM (1992), NICHOL (1996), GALLO ET AL. (1993a, 1993b, 1995), WENG ET AL. (2004), WENG & QUATTROCHI 2006, WENG 2009, OGASHAWARA & DA SILVA BRUM BASTOS 2012). In order to better understand the urban microclimate, which is itself significant to a range of issues and themes in Earth science, such as global environmental change and human-environment interactions, and also important for urban planning and management purposes, a greater assessment of the overall urban thermal pattern, including an analysis of the thermal properties of individual land covers, is still needed (GLUCH ET AL. 2006, LO & QUATTROCHI 2003, WENG & QUATTROCHI 2006).

Remote sensing data have also been used in attempts to mapping, measuring and monitoring urban vegetation surfaces (e.g., NICHOL & WONG 2007, NICHOL & LEE 2005, PHINN ET AL. 2002, SMALL & MILLER 2000, SMALL 2001, POZZI & SMALL 2002, RASHED & JÜRGENS 2010, SONG 2008, ZHU ET AL. 2003, XIE ET AL. 2008, LI ET AL. 2010B). Vegetation is an essential part of the urban and suburban environment and therefore an important parameter for the assessment of urban environmental quality (NICHOL & WONG 2007b). Variations of vegetation abundance and distribution within urban areas may influence environmental conditions "by selective reflection and absorption of solar radiation […] and by modulation of evapotranspiration" (SMALL & MILLER 2000). Urban vegetation has a strong influence on energy demand and development of urban heat islands, and may affect urban climate and urban ground energy fluxes (ABDOLLAHI & NING 2000, AKBARI ET AL. 2001, SMALL & MILLER 2000). In addition, vegetation within urban areas plays an important role in controlling temperatures and air quality (JI ET AL. 2007), and influences thus human health (WAGROWSKI & HITES 1997). Various remote sensing data have proven effective for mapping and monitoring urban vegetation abundance. For example, SMALL & MILLER (2000) have presented preliminary results of spatiotemporal analysis of urban vegetation distribution in New York City using Landsat TM data and discussed implications for environmental monitoring of developing urban areas. ZHU ET AL., however, present a method based on advanced segmentation techniques and classification for urban vegetation investigation extraction. Utilizing satellite data of the ASTER sensor, the authors build a hierarchical multi-resolution structure in order to reflect the inherent relationship between ground features under different levels of scale. Recently, a number of remote sensing scientists have explored the relationship between environmental parameters and population characteristics in urban areas. POZZI & SMALL (2002), for example, have considered vegetation abundance and population density as "principal demographic and physical characteristics" in urban and suburban areas of the U.S.A. The authors pointed out, amongst other things, that maximum vegetation fraction decreases with increasing population density over the full range of densities. Moreover, the percentage of urban vegetation can be linked to different levels of quality of life. While a large fraction of vegetation cover is associated with a high quality of life, sparse vegetation cover in a settlement is mostly, particularly in developing countries, an expression of poor living conditions. Accurate, reliable, and reasonable data of urban vegetation cover support decision makers and urban researchers with different specializations to achieve their objectives. Hence, urban vegetation research using remotely sensed data plays a fundamental role in environmental protection, urban planning and quality of life assessment (ZHU ET AL. 2003).

But with remote sensing, not only the direct measurement of physical quantities is possible. Several studies have demonstrated the ability to extract also socio-economic parameters, either directly from remotely sensed data or indirectly by means of surrogate information derived from images (COWEN & JENSEN 1998) (cf. chapter 3.3). One of the most important of these socio-economic parameters is population. Population estimations can be derived at local, regional as well as national levels based on different analysis methods (LO 1995). A general overview of the derivation of population estimates is presented in chapter 3.3. Some studies have as well shown how quality of life indicators, such as income, education, health care or house value, can be calculated by extracting several variables from ultra and very high-resolution remote sensing imagery (cf. Table 3-2) (MONIER & GREEN 1953, GREEN 1957, TUYAHOV ET AL. 1973, HAACK 1997, JENSEN & COWEN 1999, NICHOL & WONG 2007b, BROWN ET AL. 2014). For example, building size and density, vegetation surface and density, unpaved road, road width as well as proximity to work and hospital are examples for variables which are visible in remotely sensed images. These variables derived from remotely sensed data need to be validated with in-situ observations to compute the quality of life indicators and to assess the living conditions of people in different residential areas (COWEN & JENSEN 1998). In an early attempt to relate remotely sensed signatures to socio-economic parameters, FORSTER (1983) developed for instance a classification scheme which could be applied to urban areas to provide a residential quality index.

The mapping of different settlement types within urban areas is therefore closely connected with the detection of quality of life indicators. Especially in mega cities the living conditions of the residents vary widely, and thus the visible contrasts between different settlement types are very strong. To detect and describe the different types of residential areas appearing in remote sensing derived images in the most cases the pixels' spectral information solely is insufficient. Different authors, as for example HOFMANN (2001a), are of the opinion that other characteristics such as shape, texture or contextual information is required to map and analyze these areas adequately (cf. chapter 3.2.2). Formal, i.e. legal, settlements are mapped and monitored in most cases sufficiently, particularly in cities of more developed countries. However, this quantity and quality of information is, if at all, only rarely available for informal settlements. Especially the mapping and analysis of those residential areas might be one of the most challenging tasks within urban remote sensing (HOFMANN 2001a). Informal settlements show typical textural and structural characteristics (cf. chapter 2.4) which are mainly an effect of their illegal status and a direct reflection of the social circumstances the inhabitants live in (HOFMANN 2001a, TAUBENBÖCK ET AL. 2009). Hence, depending on the remote sensor's spatial and spectral properties, it is possible to classify and distinguish these areas from other land use or settlement types. The spatial location of informal settlements has already been carried out in different ways using remotely sensed data (e.g., HALL ET AL. 2001, HOFMANN 2001a and 2006, JAIN ET AL. 2005, LEMMA ET AL. 2006, MASON & FRASER 2003, NETZBAND & RAHMAN 2009, NIEBERGALL ET AL. 2007 and 2009, RADNAABAZAR ET AL. 2004, SLIUZAS ET AL. 2008a, 2008b, STEWART & KUFFER 2007, TURKSTRA & RAITHELHUBER 2004, BAUD ET AL. 2010, KIT & LÜDEKE 2013). In some cases more detailed information is necessary, so that, for example, single settlement units are detected (LI & RÜTHER 1999, MASON & BALTSAVIAS 1997). For both applications, ultra or very high-resolution remotely sensed image data is needed. Moreover, additional useful data sources such as local knowledge, field observation data, and available local socio-economic data can provide valuable information and can therefore support the location and analysis of informal settlements (LEMMA ET AL. 2006, NIEBERGALL ET AL. 2007 and 2009, ROGERS ET AL. 2006) (cf. chapter 6.2). As explained, several studies have exemplified the possibilities to use remote sensing techniques for poverty mapping and obtaining detailed information. Nevertheless, with permanently increasing urbanization rates as well as widespread and rapid development of informal settlements, it is important to develop more efficient, either fully or semi-automated, methodologies and algorithms for the detection and monitoring of informal settlements. Since particularly the conjunction of remote sensing data with socio-economic data is (still) at the beginning of the development (see chapter 3.3 and 3.4), an advancement in this research field is required. In order to carry out the demanding urban planning and development tasks necessary to improve the living conditions for the poorest worldwide, the research may never stagnate (HOFMANN 2001a, ROGERS ET AL. 2006, SLIUZAS ET AL. 2008a).

In the recent past the potential of remote sensing was also shown in the field of vulnerability assessment and disaster management. Since by now more than half of the world's population lives in urban settlements (cf. chapter 2.1), especially in these areas further information and spatial data is needed in order to support decision makers in general or in the pre-disaster phase as well as for crisis management in the post-disaster phase (TAUBENBÖCK ET AL. 2006). An analysis by DEGG (1992) of the world's 100 most populated cities pointed out that about 78 percent were exposed to one out of four major natural hazards (earthquakes, volcanoes, tsunamis, and windstorms). In less developed countries alone, 86 percent faced even more than one natural hazard (cf. chapter 2.3). The value of remote sensing in supporting urban vulnerability analysis and disaster management is evidenced by a steadily increasing number of published articles on this topic. For examples see TAUBENBÖCK ET AL. (2006, 2007, and 2008) as well as GAMBA ET AL. (2007a and 2007b).

All facts considered, urban areas are and will probably always be characterized by heterogeneous, convoluted and unpredictable land patterns. Thus, urban areas are confronting remote sensing scientists as well as planners, engineers, environmentalists, government agencies, social scientists, demographers, economists and politicians with a major task which will keep the future generation very busy (MESEV 2003 after DAVREAU ET AL. 1989 and DONNAY 1999, LIVERMAN ET AL. 1998).

3.2 Technical and Methodological Development and its Impact on Urban Remote Sensing

As described in chapter 3.1 remote sensing data and research results have been successfully applied to map urban features, to capture different land cover types, and to characterize land use patterns or urban infrastructure as well as to monitor urban environmental problems. From these applications secondary socio-economic parameters and the elements of urban infrastructure, which are not directly visible in image data, can be derived (cf. chapter 3.3) (COWEN & JENSEN 1998, HEROLD ET AL. 2003, WENG & QUATTROCHI 2007). Hence, remotely sensed image data in some applications may even be the only reliable source for a sustainable monitoring of urban settlements (MOELLER 2005). However, accurate and operational mapping and modeling of urban features and (intra-urban) processes still confront us with some major challenges. One of the difficulties in the investigation and remote sensing of urban areas is caused by the heterogeneity most urban features exhibit (cf. chapter 3.1). Hence, urban features vary substantially with regard to their object-wise spectral variance. "Object size and heterogeneity are often related" (HOSTERT 2007). Compared to objects usually found in scenes of rural environments, like forest areas, inland waters, or agricultural crop land, objects of urban areas, such as cars, residential buildings or streets, are relatively small. Although the mixed-pixel-problem is dependent on the pixel size, the problem is still much higher in urban image data. Moreover, the combination of natural and anthropogenic materials as well as the problem of shadows and shading in the built environment limits the (semi-) automated mapping and modeling of urban environments. All things considered, essential and predominant are therefore enhanced data quality and availability and the need for improved methods and analysis techniques in urban remote sensing (HEROLD ET AL. 2003, HOSTERT 2007, and SMALL 2003).

3.2.1 Spatial, Spectral and Temporal Resolution in Remote Sensing of Urban Areas

Sensors for remote sensing are designed to acquire information about various objects on the ground without being in physical contact with them. The sensor captures the electromagnetic radiation that is reflected or emitted by the objects to describe its characteristics (JENSEN 1996, LILLESAND ET AL. 2004, NAVULUR 2007). In the urban area, imaging using aerial photography has been prominent for several decades and has still kept its value for large-scale urban remote sensing studies (e.g., BALTSAVIAS & GRUEN 2003). By means of visual interpretation — the simplest method to extract meaningful information from remotely sensed data — comprehensive information about urban patterns and land use characteristics may be yield (HEROLD 2004, HURSKAINEN & PELIKKA 2004, MESEV 2003). Precondition for the application of this method is broad background knowledge of an experienced interpreter (for more details see for example HAACK ET AL. 1997 and the explanation following in chapter 3.2.2 within this study). Recent years have shown the development from analog (film-based) to digital sensors to picture the Earth's surface (cf. Table 3-2). Using digital remote sensing the image analysis became (semi-) automated and suitable for application over much larger domains (HEROLD 2004, NAVULUR 2007).

"From a historical remote sensing perspective, early attempts to acquire the" Earth's surface "from above have traditionally focused on urbanized areas" (HEROLD 2004). In 1858, Gasper Felix Tournachon, a French photographer, took over Paris the first known aerial photograph from a balloon and therefore also the first aerial "remotely sensed image" (BOWDEN ET AL. 1975, HAACK ET AL. 1997). According to contemporary documents it has been found out that single buildings could be clearly seen in these pictures. Several images of different urban settlements were captured in the middle of the 19th century "and showed not only the first remote sensing images ever, but also the earliest remote sensing of urban areas" (HEROLD 2004). A revolution and a new era of Earth's remote sensing signaled the availability of satellite derived remote sensing data and the development of adequate digital analysis methodologies in the early 1970's and the two following decades (cf. Figure 3-1). However, in this fact it must be considered that this progress did not or only partly incorporate urbanized areas. Besides the obvious but mostly top-secret military use and development of remote sensing, over the past decades, the majority of commercial remote sensing work had been focused on natural environments. Applying remote sensing technology to urban areas is therefore relatively new. The beginnings of detailed remote sensing of urban areas as a scientific or applied field were in the 1990's and within the last ten to twenty years this development is rapidly gaining in interest within the remote sensing community. While the continuous worldwide urbanization process came more and more into the focus, new promising remote sensing image sources (cf. Figure 3-1) as well as complete time series with a large retrospective time frame and more capable techniques (cf. chapter 3.2.2) became available and provided new capabilities and options in urban mapping and monitoring (DONNAY ET AL. 2001, HEROLD 2004, NAVULUR 2007, WENG & QUATTROCHI 2007).

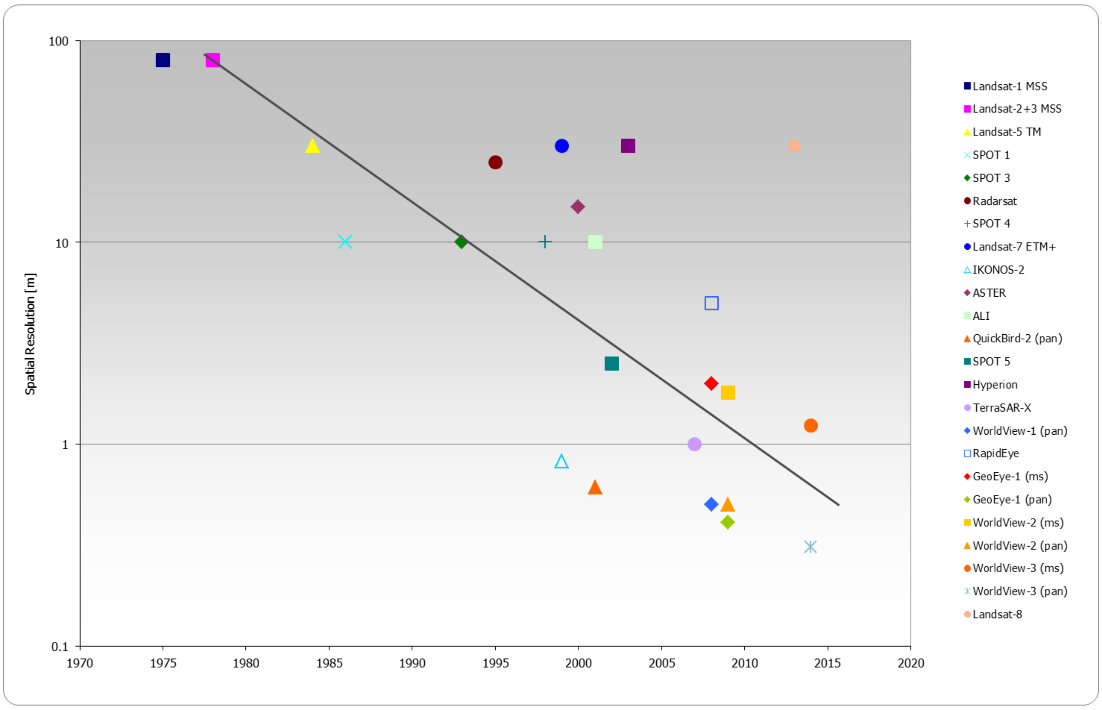


Figure 3-1: Progress of remote sensing spatial scale of civilian Earth observation satellites.

Driven by societal needs and the described progress in technology, international symposia on remote sensing of urban areas (since 1997) and remote sensing and data fusion (since 2001) have evoked great interest in urban remote sensing capabilities.

Recently, several monographs dedicated to remote sensing of urban areas appeared (e.g., BHATTA 2010, DONNAY ET AL. 2001, GAMBA & HEROLD 2009, MESEV 2003, NETZBAND ET AL. 2010, RASHED & JUERGENS 2010, YANG 2011, WENG 2014, WENG & QUATTROCHI 2007) and a number of journals have published special issues on this topic.

It is essential that the user of remotely sensed images is proficient in selecting the adequate data source in order to apply available data for his purposes effectively. This requires a comprehensive knowledge of the spatial, spectral, and temporal dimension of an object or process (cf. Table 3-2 and Table 3-3) (NAVULUR 2007). Thus, in the following, the mentioned dimensions of remote sensing images are presented. Moreover, the importance of each of the data dimensions on information extraction from an image will be discussed. The spatial, spectral, and temporal resolution requirements for the urban attributes are summarized inTable 3-1. In the best case, "there would always be a remote sensing system that could obtain images of the terrain that satisfy the urban attributes' resolution requirements" (JENSEN & COWEN 1999). In reality, though this is not possible at all.

Table 3-2: Taxonomy of Remote Sensing Systems

Recording Platform	Satellite/Shuttle		Aircraft			Stationary	
Recording Mode	Passive (Electrooptical, Thermal Infrared, Thermal Microwave)			Active (Laser, Radar)			
Recording Medium	Digital (Whiskbroom, Pushbroom)			Analog (Camera, Video)			
Spectral Coverage	Visible/Ultraviolet		Reflected Infrared		Thermal Infrared		Microwave
Spectral Resolution	Ultraspectral > 250 Bands		Hyperspectral 100 - 250 Bands		Superspectral > 10 Bands	Multispectral 2 - 10 Bands	Panchromatic 1 Band
Radiometric Resolution	Very High (> 16 bit)		High (12 - 16 bit)		Medium (6 - 12 bit)		Low (< 6 bit)
Spatial Ground Resolution	Ultra High < 0.5 m	Very High > 0.5 - 1 m	High > 1 - 4 m	Medium > 4 - 12 m	Low > 12 - 50 m	Very Low > 50 - 250 m	Extremely Low > 250 m

Data sources: Ehlers (2007) and Moeller (2005), modified

The *spatial dimension* of a remote sensing image — often expressed in terms of ground sampling distance (GSD) — corresponds in size to the area captured on the ground by a single pixel. The ground cell size of one pixel is dependent, for example, on the sensor field of view (IFOV) or the sensors flying altitude. In addition, the sensor's spatial resolution varies with the off-nadir viewing angle and the terrain on the Earth's surface has an effect as well. As mentioned before, remote sensing image data can be derived from airborne or spaceborne sensors. While aerial sensors are able to acquire image data with varying resolutions by flying at different altitudes, satellites are flying in a fixed orbit and are therefore characterized by a fixed spatial resolution at nadir. At present, different terms are circulating that refer to types of remote sensing spatial resolution. Table 3-2 and Table 3-3 generate an overview of the categories of the spatial resolution of remotely sensed image data. Rough numerical guidelines for the definition of spatial resolution used in urban remote sensing applications particularly are: (1) low resolution — defined as pixels with GSD between 12 m and 50 m, (2) medium resolution — GSD in the range of 4.0 – 12 m, (3) high resolution – characterized by an 1.0 – 4.0 m GSD, (4) very high resolution – ground cell sizes between 0.5 and 1.0 m, and (5) extremely high resolution – pixel sizes < 0.5 m (MOELLER 2005, NAVULUR 2007).

Table 3-3: Spatial Resolution of Remotely Sensed Image Data and Application Scale

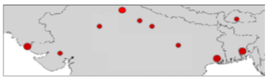
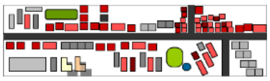
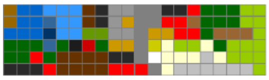
Pixel Size	**Definition**	**Sensor Platform**	**Application Scale**
< 0.5 m	Extremely high	Airborne scanner, aerial photos, GeoEye-1 (pan), WorldView-3 (pan)	1:500 - 1:5,000
> 0.5 - 1.0 m	Very high	IKONOS (pan), QuickBird (pan), WorldView-1 & 2 (pan), QuickBird-2 (pan)	1:5,000 - 1:10,000
> 1.0 - 4.0 m	High	IKONOS (ms), QuickBird (ms), SPOT 5 (pan), GeoEye-1 (ms), WorldView-2 & 3 (ms)	1:10,000 - 1:15,000
> 4.0 - 12 m	Medium	IRS (pan), SPOT 4 (pan), SPOT 5 (ms), RapidEye	1:15,000 - 1:25,000
> 12 - 50 m	Low	ASTER, IRS (ms), Landsat-7 ETM & Landsat 8 (pan, ms), SPOT 4 (ms)	1:25,000 - 1:100,000
> 50 - 250 m	Very low	Landsat MSS	1:100,000 - 1: 500,000
> 250 m	Extremely low	NOAA, Envisat	> 1:500,000

pan - panchromatic, ms - multispectral
Data source: MOELLER (2005), supplemented and modified

The spatial resolution plays an important role in the processes and objects that can be observed and respectively identified using remotely sensed images. This means that different applications require the use of different spatial resolutions. "In any application, optimal remote sensing data spatial characteristics are defined by the smallest homogeneous object of interest or some spatial ground sampling function" (HEROLD 2004). This fact is particularly important in regard to the diversity of available remotely sensed image data. Moreover, the steadily increasing number of specialized and application optimized image processing algorithms should be considered in this issue. In this context, Herold (2004) pointed out that the detection and analysis of real world phenomena at different scales requires the investigation of resolution dependent variables and critical spatial resolutions. After Davis & Simonett (1991) remotely sensed image data are applied to the following three major tasks: (1) detection — determination of the presence of an image object, (2) identification — labeling an image object, and (3) analysis — obtainment of detailed information about an image object beyond its initial detection and identification. A general spatial resolution rule for detecting an urban object in an image is that there need to be a minimum of one to four spatial observations, i.e. image pixels. Specified another way, the image detection requires a sensor spatial resolution with one-half the diameter of the smallest object-of-interest. For example, to detect small residential buildings that have a base area of 10 m by 10 m, the minimum GSD of imagery without haze or other problems should be ≤ 5.0 m by 5.0 m. The identification of object features usually needs five or more image elements. Another rule of thumb states that for object analysis a 10 times higher effective spatial sensor resolution is needed than it is required for the identification and as much as 30 times as higher resolution as for the detection of image objects (COWEN ET AL. 1995, Jensen & Cowen 1999, Herold 2004, Davis & Simonett 1991). Using different remote sensors and therefore different spatial resolutions several application problems can appear. For example, if the pixels' spatial resolution is too coarse and fails to correspond to the spatial characteristics of the image target the so called "mixed pixel problem" occurs. The mixed pixel problem — where several types of land cover/use are contained in one pixel and therefore only a generalized and regularized description of the image features is provided — decreases the accuracy of remotely sensed image mapping and analysis (for this issue see also the section "spectral resolution" below-mentioned within this subchapter) (MATHER 1999, MELESSE ET AL. 2007, HEROLD 2004). In contrast, limitations using remote sensing data become apparent as well if the sensors' spatial resolution is too fine. In that case, the image collects more spatial land surface variation than it is needed for a given analysis and thus an "image information overload" can be produced which may decrease image analysis accuracy (HEROLD 2004).

Remote sensing as a data source for urban applications at a *super-regional* and *global scale* — from 1:100,000 to 1:500,000 and more — requires image data with a spatial resolution of minimum 50 m through 250 m and beyond that value (cf. Table 3-3). HEROLD ET AL. (2006) even quote a value of minimum 30 m (cf. Table 3-4). Remotely sensed images for super-regional and global scale have already been used in many applications. For example, optical sensors (MODIS, MERIS, Landsat ETM+ and Landsat 8 etc.) have demonstrated their capability in mapping the full dimension of urban areas at the super-regional scale (e.g., SCHNEIDER ET AL. 2003, POURSANIDIS ET AL. 2015, MERTES ET AL. 2015). Moreover, active radar imagery (GREY ET AL. 2003), thermal measurements (HAFNER & KIDDER 1999), and nighttime remote sensing images have been used for global and continental purposes (SUTTON ET AL. 1997). In the latter case, data products of spatial urban extent and population density have been yielded.

Table 3-4: Observing multi-scale dynamics for mapping and modeling urban objects and processes using remotely sensed image data

Level	**Unit**	**Spatial resolution**	**Temporal resolution**	**Attributes measured by remote sensing**	**Urban dynamics**
	Global/regional networks	1 km	10 - 50 years	location of (large) settlements and their surrounding environment	super-regional and global urban dynamics: growth, diffusion, urbanization, …
	Urban/ settlement systems (regional)	30 m - 1 km	5 - 10 years	number of settlements with various spatial dimensions, utility and transportation networks	regional urbanization: interactions/polarization
	Urban area	5 m - 30 m	2 - 5 years	classification: impervious/not impervious surface, vegetation, open space, …	change detection: urban shrinking, urban growth, sprawl, diffusion, coalescence, expanding urban land uses into rural areas > urbanization
	Land use region	5 m	2 - 5 years	land use classes/categories: residential/commercial buildings, transportation network	land use change: infill/redevelopment, …
	Urban land cover objects (settlement, district, block)	1 - 5 m	1 - 2 years	transportation network components, built-up structures (medium - large buildings, building blocks), parks, gardens, utility lines	land cover change: building (re)construction, demolition of informal settlements, …
	Image Element/ Pixel	0.5 - 1 m		small buildings, trees, cars,…	material change: aging/roofing, … land cover change: (re)construction of small buildings

Source: after HEROLD ET AL. 2006, modified.

For large area applications such as urban growth monitoring and change detection a geographic scale of about 1:25,000 – 1:50,000 should answer the purpose (SABINS 1996). According to Table 3-3, this application scale is provided by sensors of the second generation like ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer), SPOT (Système Probatoire d' Observation de la Terre), and Landsat TM (Thematic Mapper) as well as Landsat 8 which offer a spatial resolution of 4.0 m to 50 m (medium to low dimension) and large swath widths. Image data of this dimension supports urban remote sensing of a *regional scale*, which is often focused on a specific urban area or agglomeration or their periphery, and provides according to HEROLD (2004), for example, a spectral separation of built-up and non-built-up urban land cover features or according to NAVULUR (2007) a large area change detection. For more details of "measurable" urban attributes and the corresponding derivable urban dynamics please see Table 3-4 below. Low and medium resolution data sources have been used to study a variety of urban phenomena like: eco systems, urban climates, urban population, health and disease, urban growth and change processes (HEROLD & SCHMULLIUS 2005).

It is also important to keep in mind that the spatial resolution and swath width are in close connection to each other. Usually, the higher the resolution is, the smaller is the size of the image. Thus, medium resolution satellite sensors such as Landsat (185 km swath) and SPOT (60 km swath) are able to provide wide area coverage necessary to capture an entire city with a single record. Hence, the researcher has the ability to use this data for comparative analysis of urban morphology. The sensors provide also the spatial and temporal resolution to support a two decade record of urban land cover change. However, medium resolution sensors lack the spatial resolution to monitor urban land cover objects and infrastructure (NAVULUR 2007, MILLER & SMALL 2003). Hence, medium resolution and smaller "have traditionally been seen as one of the major obstacles to precise urban mapping using remote sensing data" (MESEV 2003).

Some regional and a multitude of local urban applications require high-resolution (HR) remotely sensed images respectively in order to map urban land use structures and attributes in more detail. According to MOELLER (2005), a geographic scale of about 1:10,000 – 1:15,000 should be suitable for an accurate spatial representation and analysis of urban land cover objects such as different building structures, urban vegetation patches like parks and gardens, and transportation network components (cf. Table 3-4). Moreover, based on the experience of several remote sensing scientists and qualitative examinations of different urban studies, a spatial sensor resolution of 5.0 m and finer was suggested for a detailed mapping of urban land cover objects, which corresponds to the above presented geographic scale (e.g., JENSEN & COWEN 1999). Also WELCH (1982) carried out a resolution analysis of various satellite sensors and demonstrated that a GSD of 0.5 m to 10 m is necessary to characterize infrastructure in most urban areas in a detailed way. A number of sensors are providing corresponding GSD: IKONOS (ms), GeoEye-1 (ms), QuickBird 1 (ms), WorldView-2 & 3 (ms) and SPOT 5 (pan) (cf. Table 3.3). Several studies have demonstrated the potential of current sources of high spatial resolution data for measuring the physical structure and composition of cities. Appropriate examples were introduced by APLIN (2003), MEAILLE & WALD (1994) or ROESSNER ET AL. (2001).

Recent developments in satellite remote sensing offer new opportunities to capture small urban features and structures with an improved spatial resolution (cf. Figure 3-1 and Figure 3-2). The availability of commercial very high-resolution (VHR) as well as extremely high-resolution satellite data at the sub-meter level, for example IKONOS (pan), QuickBird-1 & 2 (pan)[4] (cf. chapter 5.1 and Table 5-1), WorldView-1 & 2 (pan)[4], and GeoEye-1 (pan), enable since the 21st century the chance to identify recent small-scale land use structures and dynamics in mega cities at *local scale* (cf. Table 3-3 and Table 3-4). This is especially valuable in data poor environments, which means in developing countries (cf. chapter 3.3)

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[4] DigitalGlobe currently operates the QuickBird satellite, which can collect panchromatic images with 0.61 m resolution at nadir. The satellite, launched in October 2001, also collects multispectral images with 2.5 meter resolution. Operated by Digital Globe as well, WorldView-1, launched in 2007, is a high-capacity, panchromatic earth imaging system features half-meter resolution imagery and is therefore the subsequent operation of QuickBird. Digital Globe´s satellite WorldView-2, launched on October 8th, 2009 has in addition the possibility of recording multispectral image data in eight spectral ranges with a spatial resolution of 1.8 m. The data flow of VHR data is therefore secured.

(MESEV 2003, TURKSTRA & RAITHELHUBER 2004). According to ROSSI (2003) "the full commercial availability of VHR satellite data has opened up a number of new opportunities for the use of Earth observation data" and may be therefore considered as a new era of civilian satellite remote sensing, with potential in particular for applications in urban studies (DONNAY 2001, HEROLD 2004, MEINEL ET AL. 2001, VOLPE & ROSSI 2003). The further development and subsequent operation of the so called "third generation space borne sensors" has attracted considerable interest from the remote sensing community (APLIN 2003). Hence, a significant number of studies have reported on the benefits of VHR satellite sensors applied to urban areas. Several authors have already utilized VHR satellite data to extract land cover as well as land use related information. For example, VAN DE VOORDE ET AL. (2004) carried out a study on the city of Ghent, Belgium, whereas REGO & KOCH (2003) worked with images of the city of Rio de Janeiro, Brazil. VHR remote sensing data are moreover used for urban feature extraction and identification of small objects (e.g., QUINTILIANO & SANTA-ROSA 2003, ALKAN ET AL. 2008), for mapping of impervious surface and built-up area (e.g., YUAN & BAUER 2006, LI ET AL. 2010) as well as for the detection and monitoring of informal settlements (e.g., HOFMANN 2001a, LEMMA ET AL. 2006, BAUD ET AL. 2010, KUFFER ET AL. 2013) or disaster and vulnerability assessment (e.g., GAMBA ET AL. 2007B, TAUBENBÖCK ET AL. 2007, 2008 & 2011, GEIß & TAUBENBÖCK 2013, and MÜCK ET AL. 2013) (cf. chapter 3.1 and 3.3). Moreover, data of VHR optical satellite sensors provide a viable alternative to generate digital surface and digital terrain models (ALOBEID & JACOBSEN 2008). Hence, various studies have shown that VHR image data, primarily because of its panchromatic band, allow for high precision in urban mapping and analysis. In turn, this proves that VHR images are representing an alternative to aerial photography for detailed applications in the urban environment (BAUER & STEINNOCHER 2001).

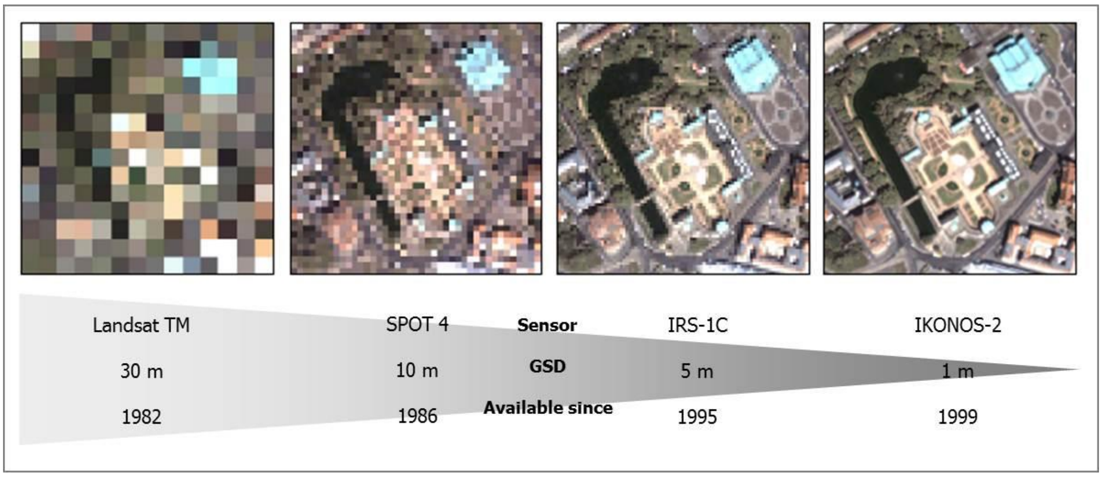

Figure 3-2: Development of ground sampling distance (GSD) of selected remote sensing satellite sensors *(Source: NEUBERT 2005, modified)*.

Moreover, it should be recognized that diversity not only is present within but also between urban landscapes which makes it impossible to advocate for specific remote sensing data or a general classification system. The heterogeneity — in terms of its spatial and spectral properties — is not only visible within one city; urban environments also vary externally according to their location. For example, the sprawling landscapes of Asian mega cities (CHEN ET AL. 2000) are very different to the densely packed cities of Europe (FORSTER 1983) and the expansive North American urban areas (MASEK ET AL. 2000, SMALL 2003). "Spatial resolution requirements for urban areas will vary considerably according to land use and location and, as such, any example of urban classification analysis should be considered in the context of its study area" (APLIN 2003).

The usefulness of a given type of remotely sensed imagery for detecting, identifying, and analyzing very specific types of urban information should not be judged solely by its spatial characteristics. In addition to the geometric elements and therefore the spatial resolution of images, the spectral response acquired by the remote sensor should be taken into consideration for characterization and analysis of urban land surface objects (JENSEN & COWEN 1999, HEROLD 2004). The *spectral resolution* refers to the number of spectral bands, their band widths and locations along the electromagnetic spectrum (EMS) (cf. Appendix, A.2). Most of the former and current airborne and satellite based sensors capture in the visible and infrared (IR) regions of the EMS. According to the number and location of spectral bands, different terms are used for sensors in the remote sensing community. For example, the term "multispectral" is commonly used for remote sensing sensors that are equipped with up to ten spectral bands (cf. Table 3-2). Each band is sensitive to radiation within a narrow wavelength band. The resulting image is a "multilayer" image which covered both the brightness and color (spectral) information of the targets being observed. Several multispectral systems offer worthwhile capabilities for urban applications. Examples are amongst others the optical sensors Landsat TM and ETM+ (Enhanced Thematic Mapper), SPOT as well as RapidEye, IKONOS and QuickBird. Although the spatial resolution of the multispectral Landsat TM system is too coarse for identification of fine urban infrastructure elements, the images are, foremost because of its spectral information, suitable for the detection of significant spatial and temporal variations in urban vegetation and surface temperature (SMALL 1999, SMALL & MILLER 2000, ANIELLO ET AL. 1995). Moreover, Landsat TM data were for instance used for assessing urban land cover changes (MØLLER-JENSEN & YANKSON 1994), the detection of pockets of urban poverty (HALL ET AL. 2001) as well as in conjunction with census data for quality of life assessment (LO & FABER 1997). Exemplary studies using Landsat ETM+ are presented for instance by FORSYTHE (2003), YIN ET AL. (2005), TATEM ET AL. (2005), and TAUBENBÖCK ET AL. (2009a). Due to the long lasting history of image acquisition of the Landsat sensor series this data is of very high value in terms of long term monitoring of urban growth patterns (HOFFHINE WILSON ET AL. 2003, MOELLER 2005) and urban change detection monitoring in general (HARTVICH ET AL. 2001). Urban growth is monitored also by means of multitemporal SPOT image data (e.g., KOLEHMAINEN & BAN 2008, DE JONG ET AL. 2000). As above mentioned the sensors IKONOS, QuickBird, and WorldView-2 are first and foremost characterized by very high spatial resolution. Nevertheless their multispectral information is very useful for applications in the urban environment. Particularly vegetation analyses (SMALL 2007) and studies for the identification of small-scale features such as individual roads and buildings in urban environments (SHACKELFORD & DAVIS 2003) benefit from the spectral properties of these sensors.

Again, urban environments are heterogeneous, and, because of their variety and mixture of urban materials, spectrally very complex. This phenomenon is often contained in one image element and produces the already mentioned "mixed pixel problem". Not only (and not in any case) may improved spatial sensor resolution solve this problem. Another opportunity to overcome this obstacle can be the application of "hyperspectral" image data. Hyperspectral sensors[5] acquire images in about a hundred or more contiguous spectral bands each with a small bandwidth of 10 nm (cf. Table 3-2). While spaceborne systems such as Hyperion (URL 13) and CHRIS Proba (Compact High Resolution Imaging Spectrometer) (URL 14) are mostly insufficient in their spatial resolution needed for urban applications, airborne systems such as AVIRIS (Airborne Visible InfraRed Imaging Spectrometer) (URL 15) and HyMap (COCKS ET AL. 1998) are the most advanced hyperspectral sensors available for urban studies (HOSTERT 2007). Using hyperspectral remote sensing data the precise spectral information makes it easier to identify and differentiate clearly between urban objects surfaces and at least objects themselves and they allow for precise determination of the chemical-physical material properties (MOELLER 2005, HEROLD 2004, NAVULUR 2007, JENSEN & COWEN 1999, GOETZ ET AL. 1985). In the beginning of urban remote sensing, only few remote sensing scientists have dealt with hyperspectral image data in the urban environment (e.g., BING ET AL. 1998). Those studies have turned out, that hyperspectral remote sensing systems were limited in their quality and application, and are mainly in an experimental stage. But recently, there has been an increasing interest in more detailed urban mapping using hyperspectral remote sensing. Hence, a growing number of studies have begun to benefit from the large amount of spectral information. Case studies which demonstrate that hyperspectral approaches expand the range and accuracy of urban studies are given by BEN-DOR ET AL. 2001, HEPNER & CHEN 2001, ROESSNER ET AL. 2001, BOCHOW ET AL. 2006, JUNG ET AL. 2007, FAUVEL ET AL. 2009, LULLA 2009 or HEIDEN ET AL. 2001 & 2012.

In addition to daytime optical remotely sensed data, some other spectral data types might be valuable for analysis in the urban environment, which are listed below briefly, each with corresponding examples from urban studies:

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[5] A hyperspectral imaging system is also known as an "imaging spectrometer".

- Thermal remote sensing data (e.g., WENG & QUATTROCHI 2006, XIAN & CRANE 2006, LO ET AL. 1997, OGASHAWARA & DA SILVA BRUM BASTOS 2012),
- Night-time optical remote sensing data (ELVIDGE ET AL. 2009, SUTTON ET AL. 1997 and 2007, SUTTON 1997, ANDERSON ET AL. 2010, GAO ET AL. 2015),
- Active microwave remote sensing data (e.g., HENDERSON & XIA 1997, GAMBA ET AL. 2006, ESCH ET AL. 2006, STILLA & SOERGEL 2007, CHANG & XUAN 2012), and
- LIDAR remote sensing data (e.g., MALLET ET AL. 2008, SECORD & ZAKHOR 2007, STEEL ET AL. 2001, SHAN & SAMPATH 2007, TIWARI & PANDE 2011).

More information and examples to these data types and urban applications have already been presented in chapter 3.1.

The *temporal resolution* is the third dimension of remote sensing image data that should be considered, especially when studying the urban environment. Temporal resolution is defined by the time frequency with which the same study area is covered by the sensors. An ideal sensor system would be able to cover permanently the entire Earth and would deliver this image data in real time. Until today, due to technical restrictions, such a "perfect system" does not exist and will not be realized in the near future. At present, there are two different types of sensors recording remote Earth data: (1) geostationary satellites and (2) polar orbiting systems or sun-synchronous satellites. Although images of geostationary satellites, such as Meteosat (URL 16), send real time images covering the entire globe from the North Pole to the South Pole, they are not useful for urban remote sensing applications since they provide very coarse spatial resolutions. Imaging satellites like Landsat or ASTER are launched in a sun-synchronous orbit that results in the satellite revisiting a given area of interest on the Earth at the same solar time. Typically they offer a revisit time of 16 days. Further, SPOT and sensors like IKONOS, QuickBird, and others offer side looking capabilities and have therefore the flexibility to record off-nadir, increasing the frequency of the repetition cycle up to three days. However, this off-nadir shots do not offer a true nadir view, what, in turn, limits the usage in some ways and degree. Another key parameter in terms of temporal resolution should be kept in mind. Namely the actual cloud coverage affects the quality of an image over a given study site. In tropical regions with a dense cloud layer, a clear view to the Earth's surface is mostly limited. Particularly in this latitude optical spaceborne sensors are thus unsuitable, whereas aerial sensors have the advantage of collecting data underneath the clouds and sensors with SAR capabilities may "see" through the cloud layer (JENSEN & COWEN 1999, NAVULUR 2007, MOELLER 2005). In addition, when monitoring urban areas using remotely sensed data, urban phenomena progress through an identifiable developmental cycle, for example vegetation progress through a phenological cycle, should be considered. This means that an image interpreter must be able to understand the "temporal resolution" of these urban phenomena. Finally, JENSEN & COWEN

(1999) pointed out that temporal resolution also may refer to how often city planners or managers need a specific type of information. For example, urban planners may demand for population estimations every five years in addition to the estimations offered by decennial censuses. The repetition rates for many important urban purposes required by managers are summarized inTable 3-1.

All in all, urban attributes and phenomena show specific characteristics in different spatial, spectral and temporal dimensions and can be identified and observed using diverse remote sensing data (HEROLD & SCHMULLIUS 2005). Linking different spatial scales and spectral characteristics as well as in-situ observations allows for generating data products that support local planning agencies and decision makers. This progress requires on the one hand continuity in Earth observations in all these scales and dimensions and on the other hand the continuous (further) development of new techniques and analysis methods. The following chapter will discuss this topic in more detail.

3.2.2 Enhancements of Remote Sensing Methodologies

"To understand the dynamics of patterns and processes and their interactions in heterogeneous landscapes such as urban areas, one must be able to quantify accurately the spatial pattern of the landscape and its temporal changes" (MELESSE ET AL. 2007 after WU ET AL. 2000). Preconditions for this are: (1) to have a proper standardized method to define the components of the urban surface, (2) to detect, identify, map and analyze these in a repetitive and consistent way, so that a (at best a general accepted) model of urban morphology may be developed, and monitoring and modeling their changes over time is made possible. This requirement itself calls for (3) adequate Earth observation data that provides useful information for urban applications (cf. chapter 3.2.1). Another key requirement is (4) the integrative use of Earth observation mapping and monitoring products with existing socio-economic data and information (MELESSE ET AL. 2007, HEROLD & SCHMULLIUS 2005) (cf. chapter 3.3 and 3.4, chapter 6.2 and 8).

As described in the previous chapter 3.2.1 a wealth of advancing remote sensing technologies were developed especially in the last fifteen years. Hence, a large amount of adequate Earth observation data providing valuable information for urban applications is available. But, HOSTERT (2007) has stressed in this context also that new remote sensing technologies do not, per se, lead to more advanced image analysis results. HOSTERT (2007) emphasized that "sensor improvements need always to be understood in the context of matching methodological progress, i.e., innovative data sets need to be adequately explored through adapted processing schemes". In the large majority of cases, but especially in the urban context, there is no simple or even generally admitted methodology for analyzing remotely sensed image data effectively and for extracting of useful information (HOSTERT 2007).

Today, manifold methods to extract meaningful information from remote sensing image data covering urban environments exist. However, to get there was a quite long way of technical and methodological developments. Likewise the development of appropriate pre-processing techniques (for urban applications), the advances achieved in methods of information extraction have been considerable during the last ten years (HOSTERT 2007).

At the beginning of urban remote sensing, detailed and accurate information about urban land cover and land use was provided by *visual interpretation* of aerial photographs (cf. chapter 3.2.1). Visual analysis is until today the simplest method to yield meaningful information from remotely sensed data (HEROLD 2004, HURSKAINEN & PELIKKA 2004, MESEV 2003, NEUBERT 2005). After PHILIPSON (1977 quoted in JENSEN 2006) visual interpretation can be defined as "the science and art of observing images with the objective of identifying different objects and judging their significance". Although as old a method as interpretation of remotely sensed data itself, visual interpretation is still beneficial for all scales of urban remote sensing studies, "at least as a method available when all other methods fail or are not available for some reason" (HURSKAINEN & PELIKKA 2004). Moreover, this method is used for visual validation and evaluation (cf. e.g., chapter 5.3, 6.1.1 and 7.1.1). Precondition for the application of this method, and thus for visually interpreting textural, contextual and spatial configurations of urban features, of course is broad background knowledge of an experienced interpreter (HAACK ET AL. 1997). The interpreter evaluates the following features to identify meaningful image components (ALBERTZ 2001, HILDEBRANDT 1996):

- Color and color saturation (or rather brightness and differences in brightness using panchromatic image data),
- Texture and pattern,
- Object shape and size,
- Absolute and relative location,
- Shadow,
- Association (in the conjunction with context information, e.g. proximity to objects or neighborhood relations), as well as
- Vestiges of human utilization, cultivation, and planning (cf. Table 3-5).

The essential advantage of the visual analysis is that not only an isolated spot within the image is examined but the context information is considered as well. The simultaneous collection of different image object features enables even the recognition of highly complex circumstances and hence a very good and extensive extraction of the information content of the image data is achieved. Drawbacks of this method include slowness, and a low cost/efficiency ratio (HURSKAINEN & PELIKKA 2004). Although this approach requires only about a quarter to a fifth as much time as terrestrial mapping (BUDER 1998), it is much more time consuming than computer-based methods. Another disadvantage is the image interpreter's lack of objectiveness. Discrepancies in expert knowledge, visual sensitivity and different image interpreters' ability to judge, result in different outcomes. Detailed information about visual interpretation is documented for instance by HAACK ET AL. (1997) or HEROLD (2004).

Recently, *digital image processing techniques* have been widely applied in urban land cover and land use classification and change detection. Much of the expert knowledge of the human image interpreter, continuously derived during remote sensing enhancements, is translated into the (semi-) automated digital analysis of satellite imagery. Digital techniques can of course go beyond the capabilities of human interpreters, particularly in generation of quantitative and consistent indicators and relationships of spatial land cover features. This potential may "provide a new level of understanding of urban form and improved mapping products" (HEROLD 2004). In digital image interpretation and analysis two main methods are available: (1) the statistical approach, based on the image and pixel histogram values respectively and (2) the image object-based approach.[6]. In the past decades, the pixel-based algorithms are the main image processing means. For *pixel-based approaches*, usually multispectral image data are used for classification, and of course, only the spectral information presented within the data for each pixel is used as the numerical basis for categorization. The multispectral classification is based on conventional mathematic-statistical techniques, such as *supervised* and *unsupervised* classification (MATINFAR ET AL 2007, APLIN2003, MOELLER ET AL. 2004, XIAOXIA ET AL. 2005). Both methods are based on the assumption that the different spectral classes are distributed in the n-dimensional image feature space (n = number of spectral bands).

Many different types of pixel-based classification analysis have been applied to urban environments. Statistical algorithms, such as maximum likelihood (ML), minimum distance (MD) or nearest neighbor (NN) have been used widely (e.g., STEFANOV ET AL. 2001, CHAN ET AL. 2001), while other classifiers such as neural networks are increasingly being implemented (e.g., GAMBA & HOUSHMAND 2001) (cf. Table 3-5).

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[6] Today several terms for the analysis of image objects extracted from remote sensing data exist. Some authors use for instance the term "segment-based" or "segmentation-based" image analysis (e.g., GREIWE & EHLERS 2004, NEUBERT 2005). Within this study the term "object-based" image analysis is preferred and used interchangeably with the term "object-oriented".

Table 3-5: Comparison of different analysis methods of remotely sensed image data

Comparison criteria	Classification methods				
	Visual image interpretation	Pixel-based classification	Per-parcel classification	Neural networks	Object-based classification
Input data required	Image data	Image data	Image and supplementary data	Image data	Image data
Main influence factor on the quality	Broad background knowledge of an experienced interpreter	Training	Training, quality of supplementary data	Training	Parameter choice
Utilization of neighborhood relations	yes	no	no	no	yes
Utilization of textures	yes	possible	possible	possible	possible
Utilization of object features (apart from spectral signatures)	yes	no	no	no	yes
Training effort	very high	medium	medium	high	medium
Automation level	low	medium	medium	medium	medium
Applicability for VHR image data	good	low	good	medium	good

Source: NEUBERT (2005), modified

Pixel-based classification algorithms are widely used, but the limitations are clear and widely known. Using this type of so called "hard classification" algorithms too many or not well defined land cover/use classes are produced and thus rarely an accuracy of greater than 80 percent can be achieved (MELESSE ET AL. 2007 after MATHER 1999, EHLERS ET AL. 2005). Especially, in the case of classifying complex urban environments with VHR remotely sensed data the pixel-based method appears not to be suitable any more. Although the use of VHR image data reduces the mixed-pixel-problem and explicitly improves the visual interpretability of details on very heterogeneous as well as compact urban areas, the internal variability and the noise within land cover/use classes is strongly increased. In turn, this effect within a thematic class or object causes other problems so that traditional pixel-based classifiers result in "speckled" classifications (so-called "salt and pepper effect") (CUSHNIE 1987, KIM ET AL. 2006, MEINEL ET AL. 2002, VAN DE VOORDE ET AL. 2004). HURSKAINEN & PELIKKA (2004) mention three factors that limit the application of pixel-by-pixel classifications of urban areas: On the one hand, pixel elements do not sample the urban area at the spatial scale of the features to be mapped, and buildings are represented by accumulations of pixels which should rather be treated as individual image objects. On the other hand, "a building produces a wide range of spectral signatures as the pixels will represent different facets of the roof" (SMITH & HOFFMANN 2001). This phenomenon appears primarily at the classification of informal settlements, where house tops are built up of diverse materials with varying texture and color (spectra) (MASON & BALTSAVIAS 1997) (cf. chapter 7.2.1). A similar challenge can represent urban road network — especially in deprived settlements of mega cities of developing countries —, where different materials alternate within single roads (cf. Figure 3-3 (2) and Figure 3-3 (3) and chapter 6.1.1). Spectral signatures of single pixels are therefore only meaningful in a limited way regarding the class affiliation of an image object (NEUBERT 2005). Moreover, many surfaces within the urban environment appear spectrally very similar (e.g., concrete roofs and asphalt roads, or buildings constructed from brick or adobe and unpaved roads or open spaces) and can thus be differentiated only by some ancillary context information (cf. Figure 3-3 (1)) (SMITH & HOFFMANN 2001). Shadows of buildings and trees (cf. Figure 3-3 (4)) as well as sun glint on roofs and interfering objects, such as cars on roads (cf. Figure 3-3 (5), may complicate classification matters even more (VAN DE VOORDE ET AL. 2004, NEUBERT 2005) (cf. introduction of chapter 3.2).

Figure 3-3: Examples for factors that limit the application of pixel-by-pixel classifications of urban environment: 1 — difficult spectral differentiation (spectral similarity of urban buildings and adjacent roads), 2 & 3 — spectral variability (urban road network characterized by different materials alternating within single roads, open space with different or mixed materials), 4 & 5 — phenomena and objects hampering image analysis (shadows of buildings and trees or cars on roads) (Data source: QuickBird test site South s3 and South s2 (4, 3, 2)).

"In order to derive useful thematic maps from VHR satellite images of urban areas, other approaches than the traditional pixel-by-pixel classification is needed" (VAN DE VOORDE ET AL. 2004). The digital classification of remote sensing data can for instance be carried out using textural image features (texture analysis). "One way to reduce the "salt and pepper effect" in a pixel-based classification is for instance to apply a standard majority filter (GURNEY AND TOWNSHEND 1983) or a more sophisticated spatial reclassification technique (e.g., BARNSLEY & BARR 1996) within a moving window or kernel of fixed size" (VAN DE VOORDE ET AL. 2004). An alternative approach uses a window with varying size as spatial effective analysis area (e.g., GONG & HOWARTH 1992, FORSTER 1993). Under consideration of adjacent pixels within a moving window or kernel (also called filter matrix or mask), textures are computed using different filter approaches from the deviations of the spatially adjacent spectral values and are assigned to the respective central pixel. Since a single pixel does not have any texture, the calculated values are not object-related textures as they are utilizable at a visual interpretation. It rather is a matter of local deviations of grey scale values which can be described as spectral texture (NEUBERT 2005, CAMP-VALLS & BRUZZONE 2009). In addition, a widely-used example of texture analysis is the computation of a co-occurrence matrix, which can be traced back to the work of HARALICK (1979, HARALICK ET AL. 1973) (cf. chapter 6.1.2).

But also the use of kernel-based approaches has a number of disadvantages. For instance, especially using a fixed window size, the difficulty of selecting an optimal kernel size plays an important role. Moreover, the fact that a rectangular window represents an artificial construct that does not refer to real spatial parcels and land units, which tend to have irregular shapes and their own distinct spatial boundaries, makes it difficult to achieve satisfying classification results (VAN DE VOORDE ET AL. 2004, BARNSLEY & BARR 1997, HEROLD 2004). "Hence, region-based approaches which use irregularly shaped areas for spatial structure characterization are especially useful in applications with homogeneous land use structures in discrete defined regions, as is found in most urban land uses" (HEROLD 2004).

Pixel-based techniques generally examine only one scale and one pixel at a time, ignoring neighborhood and concepts hierarchy. To avoid the problems related to the use of pixel-based methods an alternative way to look at the image data is required. At the same time, increasing spatial sensor resolution and "wider integration of image-derived knowledge in policy development and decision making" has increased "the need for information on land use as well as natural and anthropogenic processes" (SLIUZAS ET AL. 2008a). Hence, knowledge- rather than data-driven questions have to be answered and therefore the requirement for fundamentally different analysis techniques than previously available has increased strongly. Especially in terms of analysis of heterogeneous urban environments, including conceptual or spatial rules and conditions, a concept not supported by "classic" pixel-based approaches but identification of geometric primitives and their topology is promising and needed. For that reason, the introduction of *object-based approaches*, independent of individual pixel DN values, creating meaningful objects, incorporating shape, texture and the contextual properties as well as considering mutual objects' relationships for image classification, has evolved into a veritable alternative for remote sensing image analysis (DARWISH ET AL. 2003, HURSKAINEN & PELIKKA 2004, and SLIUZAS ET AL. 2008a). Table 3-6 presents the attributes used for classification in the object-oriented versus the pixel-based classification approaches.

Table 3-6: Attributes used for pixel-based and object-oriented image classificatiob

	Color/spectral	Form/Shape	Area/Size	Texture	Context
Pixel-based	√	X	X	X	X
Object-oriented	√	√	√	√	√

Source: XIAOXIA ET AL. (2005)

In general, an object-based image analysis process can be divided into two main work-flow steps: (1) the multi-resolution image segmentation of data into rather homogeneous and meaningful regions (objects or segments), for example, by means of the spatial and spectral characteristics, and (2) the knowledge-based classification of the produced image segments (XIAOXIA ET AL. 2005, BAATZ & SCHÄPE 2000). Since an object-oriented image analysis approach is used within this study to analyze VHR image data of the mega city Delhi, India, a detailed description of image segmentation and subsequent classification algorithms is given in the methodological part of this thesis (chapter 6.1.1 and chapter 6.1.2 respectively).

However, in order to give the reader a first comparison with "classical" image analysis methods and to explain why the OOA approach was chosen for this research, the strengths of OOA shall be provided within this chapter. Analyzing image segments instead of single pixels has significant and comprehensible advantages (cf. Table 3-5). First, meaningful image segments and their mutual relationship represent the important semantic information necessary to interpret an image in a more sophisticated way and extent than single pixels do (BAATZ & SCHÄPE 2000). SLIUZAS ET AL. (2008a) have underlined that the "real strength of OOA, however, lies in a combination of multi-scale segmentation with subsequent contextual analysis, whereby the spatial, spectral and contextual properties of extracted segments at different spatial scales are used in conjunction with spatial rules in a subsequent classification". This means that the produced image objects of an OOA "come closer to the spatial and therefore spectral and textural characteristics of the real world structures" (TAUBENBÖCK & ROTH 2007). Moreover, the OOA overcomes the problem of salt-and-pepper effects found in classification results from traditional pixel-based approaches (HOSTERT 2007, VAN DE VOORDE ET AL. 2004). Hence, several authors are of the opinion that the advantages of OOA are very useful for the analysis of heterogeneous urban environments, especially in terms of analyzing geometric VHR remote sensing data (e.g., HOSTERT 2007, XIAOXIA ET AL. 2005). At the same time, SLIUZAS ET AL. (2008a) pointed out that urban environments tend to challenge a straightforward application of OOA. For them it originates from the simultaneous excess and scarcity of information, especially in VHR image data. For example, such high detail in the image data means that urban objects of interest, such as buildings (i.e. roof materials and quality), appear with increasingly large spectral variations, hampering their automatic extraction as homogeneous regions. Vice versa, however, using only the multi-spectral band of VHR image data (e.g., the 2.44 m ms band of the QuickBird sensor, which data is applied in this study) it is not possible to detect and map many relevant urban features, especially in very dense areas occupied by small, closely packed dwelling units (SLIUZAS ET AL. 2008a) (cf. chapter 3.2.1). Here, a resolution merge of the different bands of the image data, as mentioned before within this chapter, can be a promising answer to this problem (cf. chapter 5.1.2).

The utility of object-oriented analysis (OOA) has already been demonstrated in many research fields, such as vegetation and ecological mapping (e.g., ADDINK ET AL. 2007, ATZBERGER 2004, LALIBERTE ET AL. 2004, HESE & SCHMULLIUS 2005, TAPAS ET AL. 2012), classification of agricultural areas (e.g., OZDARICI & TURKER 2006), geological and soil mapping (e.g., MAVRANTZA & ARGIALAS 2006,), resource management (MAKELA & PEKKARINEN 2001) as well as risk and vulnerability research (e.g., EBERT ET AL. 2007, TAUBENBÖCK ET AL. 2008) and hazard assessment (e.g., SUMER & TURKER 2006). Object-oriented classification methods have been also used to study a variety of urban phenomena. KUX ET AL. (2006) showed, using the example of São José dos Campos, Brazil, that OOA presents a strong potential to classify urban land cover out of VHR satellite images. Also VAN DE VOORDE ET AL. (2004) demonstrated that OOA is a useful technique for the extraction of land cover related information for urban areas. Several scientists have concentrated on mapping certain land cover classes using object-oriented methods. For example, ZHU ET AL. (2003) and YUSOF ET AL. (2008) investigated in urban vegetation extraction. YUSOF ET AL. (2008) mapped moreover open spaces in the city of Kuala Lumpur, Malaysia. Other authors concentrated on the identification and measurement of impervious areas (e.g., KAMPOURAKI ET AL. 2006, YUAN & BAUER 2006). The research of ESCH ET AL. (2005) showed the applicability of an OOA for the identification of built-up areas. Further, OOA are valuable for feature extraction such as buildings or roads (ALKAN ET AL. 2008). However, producing suitable mapping results is limited by shadow and neighbored buildings. Especially VHR image data is frequently affected by shadows, particularly in urban areas with large variations in surface elevation. Generally, it is critical to restore the radiometric response for the shaded zones before classification, or differentiate between shaded and non-shaded areas. Since shaded regions of certain land cover types show different spectral responses from those that are non-shaded, ZHOU ET AL (2009) found out that using the same procedure for classification of shaded and non-shaded areas may lead, to significant errors in urban land use/cover classification. To meet the requirements and reduce the shadow effects in urban classification, the mentioned scientists compared several methods for classification of shaded areas using object-oriented procedures. Their results are useful for users to select appropriate methods. Another application field of OOA is the monitoring of urban growth. For example, the analysis of MOELLER (2005) using long term remote sensing imagery from several sensor systems shows the capability for in depth monitoring of urban growth patterns. The outcome of this study may be a basis for the comparison of different cities with the same scheme. The transferability of stable object-oriented classification approaches is also supported by the work of TAUBENBÖCK & ROTH (2007) or MOELLER ET AL. (2004).

The results of several studies have demonstrated moreover that remotely sensed data in combination with OOA can be used to detect and discriminate informal settlements from other urban land use forms (e.g., HOFMANN 2001a, SLIUZAS ET AL. 2008a, KOHLI ET AL. 2013) (cf. chapter 3.1). SLIUZAS ET AL. (2008a) noticed in this regard that object-oriented processing has "the ability to integrate context, multi-type data (both image and thematic) and a reasoning approach similar to that of an experienced analyst evaluating images visually". Moreover, the authors pointed out that a concept of *Human Urban Patches (HUPs)* (as presented for instance by HEROLD ET AL. 2001) can be applied to map areas of urban poverty and deprivation, to asses their spatial evolution, and to derive further quantitative parameters. HUPs are areas of similar urban structure showing similar properties according to their size, shape and color, and significant variability in their density, spatial patterns and fragmentation (HEROLD ET AL. 2001, SLIUZAS ET AL. 2008a). SLIUZAS ET AL. (2008a) concluded therefore that, "provided a valid spatial description of a deprived area […], such spatial metrics can be used" for: (1) the identification and quantification of deprived/informal settlements with similarly physical entity in the same urban environment, and (2) the provision of useful information on the actual physical state within the patches, such as building area and density, vegetation fraction, or the amount of paved versus unpaved roads. Moreover, HUPs can (3) be described with respect to their proximity to public service or transport infrastructure, or other environmental parameters, such as risk exposure to hazards (cf. chapter 2.3 and Figure 2-6). Based on their changing spatial metrics it is also possible to (4) monitor changes within HUPs over time. Several authors used a HUP-related approach to describe the urban environment. For example, NOBREGA ET AL. (2006) attempted to identify roads in VHR data using an OOA, and used the paved/unpaved ratio to identify informal settlements in the mega city of São Paulo, Brazil. The preliminary findings of SLIUZAS ET AL. (2008a) show the potential of OOA to provide useful information on aspects of the physical state of HUPs. For example, information on pattern, density, and fraction of vegetation can be derived from the image data. But they also found out that more contextual information needs to be included in order to improve the description of HUPs and to relate them with levels of physical deprivation. The present study makes also use of the strengths of OOA to map homogeneous urban areas based on their topology and characteristically observable parameters (cf. chapter 6 and chapter 7). Within this research different settlement types (= different HUPs) in the mega city of Delhi, India are extracted. Hereby, since there is particularly need for action, special importance is attached on the identification of informal settlements within the urban environment (cf. chapter 4.1 and 7.2.1). Recognizing that some parameters relevant to informal settlement characterization cannot be extracted from the VHR imagery directly, an integrative data analysis using information based on questionnaires is implemented to derive socio-economic information such as population and water related parameters (cf. chapter 6.2 and chapter 8).

A comparison with other, conventional methods is likely the best way to assess the ability and quality of object-oriented classification approaches. The work of YUAN & BAUER (2006), where object-oriented and pixel-based classifications are explored and compared regarding their ability to map impervious surface areas, is a representative example for such a comparative study. They found out that the OOA produces more homogeneous land cover classes with higher overall accuracy. Since the OOA is based on fuzzy theory, its classification results were also more reasonable when dealing with mixed pixels that include more than one class. In contrast, for impervious surface mapping, the pixel-based ML classification performance seemed to be better for delineating small impervious patterns such as a single-family residential building. Since both object-oriented and pixel-based algorithms have their pros and cons, sometimes it is worthwhile combining both methods. Thus, SHACKELFORD & DAVIS (2003) presented a combined fuzzy pixel-based and object-oriented approach for classification of urban land cover from VHR multispectral image data. Another approach involves the generation of two independent but rudimentary urban land cover products, one spectral-based at pixel level and one segment-based. These classifications were then merged through a rule-based approach to generate a final product with enhanced land use classes and accuracy (GUINDON ET AL. 2004).

As described in chapter 3.2.1 hyperspectral image data with contiguous and narrow bands are needed to differentiate the subtle spectral differences in heterogeneous urban environments. The extreme variety and mixture of natural and anthropogenic materials can usually not be handled using a "classical" analysis approach of supervised or unsupervised image classification. Hence, hyperspectral image analysis tools, such as *spectral unmixing*, *spectral feature fitting*, or *spectral angle mapper*, show a great potential for analyses in urban environments based on image data providing spectral high-resolution. Detailed information on this topic can be found at HOSTERT (2010).

At the beginning of this chapter it was explained that the integrative use of Earth observation mapping and monitoring products with socio-economic data and information is a key requirement to understand the dynamics of patterns and processes and their interactions in heterogeneous urban areas (HEROLD & SCHMULLIUS 2005). Compared to Earth observation data, socio-economic data is usually without spatial reference or is spatially aggregated. An appropriate conceptual framework for data integration purposes and corresponding drivers and factors of urban processes is presented in Figure 3-4.

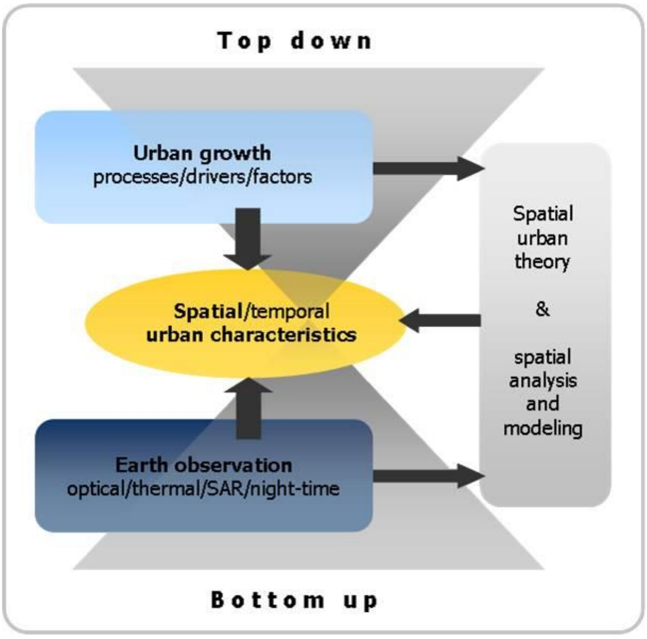

Figure 3-4: Conceptual framework for integration of Earth observation data and drivers and factors of urban processes *(modified after HEROLD & SCHMULLIUS 2005)*.

Using Earth observation techniques urban features are measured and recorded in "bottom up" direction describing the results of various processes at work. In other words, Earth observation captures the different types of urban structure and attempts to describe past and ongoing urban processes. By contrast, "socio-economic drivers or specific urban models usually follow a "top down" approach by studying a pre-specified process of urban change and the resulting spatio-temporal patterns (from process to structure)" (HEROLD & SCHMULLIUS 2005). The information derived by linking these two approaches provides an appropriate framework for mapping, monitoring, and modeling phenomena in urban environments. This information is, on the one hand, required to assess and describe social, economic, and ecological impacts of the ongoing urbanization process. On the other hand, such information has become indispensable to pre-estimate and predict future changes and trends of development in urban environments on global as well as on local scales. Not only in opinion of HEROLD & SCHMULLIUS (2005), but also in opinion of other scientists (e.g., SLIUZAS ET AL. 2008a, TAUBENBÖCK ET AL. 2009), integrative research work will support building the bridge between observation and use and will therefore make a contribution to an improved understanding which supports applied urban planning and management (DONNAY ET AL. 2001, HEROLD 2004, HEROLD & SCHMULLIUS 2005). Condition precedent for a successful integrative use of Earth observation mapping and monitoring products with existing socio-economic information is that both disciplines, remote sensing and social science, are working closer together in the future. The following chapter will explain in more detail why integrating social science and remote sensing is a promising and emerging agenda in urban research applications.

3.3 Linking Urban Remote Sensing and Social Science

In general there is an increased interest today in making scientific progress through using remotely sensed images in social science (RINDFUSS & STERN 1998). Urban remote sensing is a meeting point for social and physical sciences. Moreover, "social applications of remote sensing can inform the research agenda of the urban remote sensing arena" (RASHED & WEEKS 2003).

However, the interest in this "multidisciplinary and multisectoral urban environmental research" (MILLER & SMALL 2003) was not always as big as today (RINDFUSS & STERN 1998). Despite the apparent advantages and benefits of remotely sensed data for social applications, remotely sensed images have not been a popular data source for social science research in the past and today are still only rarely taken into consideration. According to RINDFUSS & STERN (1998), there are miscellaneous reasons for this development. First, social scientists are likely to be skeptical that remote sensing can measure anything considered important in their area of research. Visible human artifacts such as buildings, parks or roads are less interesting for social scientists than the abstract variables that explain their appearance and transformation. Variables, such as government policies, distribution of wealth and power or market mechanisms, are more important for them and are, doubtlessly, not directly reflected in remote sensing images. Secondly, social scientists are more concerned with the question why things happen than where they happen (TURNER 1991, 1998). Relatively few social scientists, despite the field of geography, value the spatial parameter that remote sensing data can provide (FAUST ET AL. 1999, GEOGHEGAN ET AL. 1998, RINDFUSS & STERN 1998). Thirdly, many social scientists do not know what a pixel is, what represents the electromagnetic spectrum, or why one needs quite often an atmospheric correction of remotely sensed images. Vice versa, the majority of remote sensing experts are unlikely to be conversant with a wide range of social problems and solutions. They have overlapped only a little with social scientists in their backgrounds, theories and methods. Thus, "integrating social science and remote sensing will require the fusion not only of data, but also of quite different scientific traditions" (RINDFUSS & STERN 1998). Finally, linking remote sensing and social science undoubtedly entails the risk frequently encountered by those who do interdisciplinary research.

Regarding this discrepancy of approaches between the two research disciplines, why should scientists of both sides anyhow try to overcome this gap and bridge social science and remote sensing? Why it is important to link people and pixels? What can remote sensing do for social science and especially for urban studies? And what can social science do for (urban) remote sensing? RINDFUSS & STERN (1998) give an idea of further ways how linking people and pixels might result in "better" social science. The authors summarize how remote sensing observations provide uniquely useful information for social research. In addition, they describe the potential practical value of social science to remote sensing as well as several kinds of scientific contributions to remote sensing that might come from its interaction with social science. In the following the topic shall be introduced briefly.

For social science experts, one crucial reason for using remote sensing images is to obtain information on the context that evokes social phenomena. The function of context has become more and more important to the theories and empirical work of numerous social scientists. The analysis of remote sensing data offers an additional source of contextual data for multilevel analyses. Contexts can be determined in different ways. Censuses are one example (WEEKS 2001, RINDFUSS & STERN 1998).

Moreover, remote sensing can provide data for various dependent attributes associated with human activity. First and foremost the environmental impacts of numerous social, demographic or economic processes. Surveillance and monitoring of land cover may present the fingermarks of road development, desertification, and deforestation as well as of course urbanization. As another example, "the observation of new building construction may be linked to the effects of local policies on land use and property taxation" (RINDFUSS & STERN 1998) as well as to the impacts of insufficient management and planning as a result of rural exodus and migration into the cities. Methods that link results of remote sensing observation with ground-based social data have the capability to improve the understanding of the parameters of different land use changes and therefore of developments in the urban environment. COWEN & JENSEN (1998) give an example for such method development in which residential development is the parameter being predicted. Thus, using remotely sensed data makes it possible to measure social phenomena and their effects.

Remote sensing can provide a number of further indicators for social science studies. These indicators can complete indicators acquired on ground. For example, urbanization can be monitored by counting buildings permits, sampling settlement blocks or remotely sensing the proportion of impervious and not impervious land (COWEN & JENSEN 1998) (cf. chapter 3.1). All data sources have their drawbacks and limitations, but the combination of various sources with different imperfections might provide a better or even complete picture of the social phenomenon (RINDFUSS & STERN 1998).

Another advantage of remote sensing images is the higher temporal and greater spatial resolution than data from other sources have. This quality can be used for instance during intercensal periods to update the census reports or to make census data generally available. In more developed countries census data are mostly very accurate, but they are collected infrequently. Sometimes, particularly in less developed countries, census data are reported inaccurately for several geopolitical or cultural reasons, or are not available at all. As a cost-effective data acquisition technology, remote sensing has been more and more used for population estimation. The early roots of research in population estimation go back to the 1950s and gained increasingly in importance since the 1970s (LIANG ET AL. 2008). COWEN & JENSEN (1998) exemplify the ability in this research field on correlations between remotely sensed indicators of dwelling units and actual census. LO (1986), CHEN (2002), HARVEY (2002a, 2002b and 2003), HOFSTEE & ISLAM (2004), SOUZA ET AL. (2002), LIU & CLARKE (2007),

QIU ET AL. (2003), WU & MURRAY 2007, LIANG ET AL. (2008), LU ET AL. (2006) or LIU & HEROLD (2007) as well as DOBSON ET AL. (2000), WANG & WU (2010) and KANJIR ET AL. (2012) give other examples for population estimation using different satellite data and methods. Thus, research has proved that remotely sensed data are efficient and effective in estimating population of urban areas. However, RINDFUSS & STERN (1998) also draw one's attention to the limitations in the use of remote sensing for population estimates. Thus, it is e.g. not possible to discriminate clearly between residential buildings and others or to sense the amount of people per housing unit or housing units per building. The latter is a subject this study also is dealing with. In order to sort out this inability, in-situ studies (household survey, cf. chapter 5.2 and ancillary field data, cf. chapter 5.3) are necessary to determine how the number of people per dwelling unit varies with the living conditions and thus with the socio-economic and physical characteristics of different settlement types. In the opinion of RINDFUSS & STERN (1998) remote sensing might help to improve population estimates, if the difference is sufficiently systematic. Whether and to which extent this is possible will show the present analysis that uses remotely sensed data of very high spatial resolution and survey data of Delhi (cf. chapter 8). Nevertheless, a number of methodological studies are necessary, before a routine use becomes possible.

Remote sensing images have been used also to obtain other significantly socio-economic parameters, especially in urban contexts. For example, traffic patterns and road conditions (DELL'AQUA ET AL. 2003, DAMM ET AL. 2005, HAVERKAMP 2002, NOBREGA ET AL. 2006, SHACKELFORD & DAVIS 2003, ZHANG & COULOIGNER 2006) (cf. chapter 3.1) as well as physical features of buildings (e.g., area or height) (CENTENO & MIQUELES 2004, TUPIN 2003) are investigated by the remote sensing community. Moreover, residential energy demand is determined or prediction models of urban expansion (CHENG 2003, CHENG & MASSER 2003, CLAPHAM 2001, GLUCH 2002, HEROLD ET AL. 2005, SILVA & CLARKE 2002) or shrinkage (BANZHAF ET AL. 2007) respectively are developed using remote sensing observation techniques. Some of these approaches and methodologies are in advanced stages, but some are still in its infancy. Hence, "more experience is necessary to determine how well they work across a variety of social and geographic conditions and over longer periods of time" (RINDFUSS & STERN 1998). These determinations "may provide important advantages in cost or temporal resolution over conventional measures of the same" features, and "may make it possible to improve the quality of modeling used for planning urban infrastructure needs and forecasting the need for utilities or other public services" (RINDFUSS & STERN 1998).

"Making connections across levels of analysis" is another aspect which speaks for the cooperation of social and remote sensing scientists. Images of space- or airborne sensors though are composed of individual pixels with different spatial resolution, but they can be combined to enable analysis at any level or scale coarser than the pixel size. Thus, remote sensing data have the ability to provide the possibility for encouraging social scientists to communicate across levels of analysis and to develop theories and methodologies that link these levels (RINDFUSS & STERN 1998).

In addition to that, more attention should be paid to the growing interdisciplinary community interested in sustainable development as well as global environmental change and related issues of human-environment interaction. This interdisciplinary community has to compare data on social and environmental aspects at the same spatial and temporal resolutions. It comprises both social as well as physical researchers. Merging social and remote sensing data should therefore be an interesting approach (RINDFUSS & STERN 1998).

From the perspective of remote sensing experts, a mandatory answer is "social utility" (RINDFUSS & STERN 1998). In order to justify the application of remote sensing it is in general adjuvant to depict the potential of this discipline of physical science for social sciences. Hence, the argument of "social utility" means an increase in reputation of remote sensing as a consequence of social scientists recognizing the advantages of applying this technology for their purposes. In this context efforts should be made to identify and bridge still existing gaps between these scientific disciplines. Furthermore, the participation of social scientists makes it possible for remote sensing experts to see the landscape from a different angle and to "discover" features in the image data not previously apparent. For the validation of remote sensing observation results ground truth data is essential. A large percentage of the required data, for instance spectral measurements of different land cover types, is collected by the remote sensing specialists itself. But there are, however, different kinds of ground truthing "that involve classifying remote observations into more obviously social categories, and thus depend on social science input" (RINDFUSS & STERN 1998). Important examples are land use classification and differentiation of land tenure. Social scientists have access to a large set of most different social data. These data can also be used for validation purposes, but in particular they can directly be linked with remotely sensed data.

Even if the linking of remote sensing and social science may bear difficulties and still is at the beginning of its development, it has been and continues to be done. There are several examples for the potential of interdisciplinary and multisectoral research evidenced by the following case studies. For example, GEOGHEGAN ET AL. (1998) show, that there are a number of opportunities to pursue some of the core social science research fields more closely through remote sensing and GIS. The authors take issues like gender, demography, (under) development, and decision making, as they relate to resource use and environmental change, as examples. For this purpose, their paper explicates various themes under development by the International Geosphere-Biosphere Programme (IGBP) – International Human Dimensions Programme on Global Environmental Change (IHDP) core project on Land Use/Cover Change (LUCC) (TURNER II 1997). The agenda of the LUCC project comprise making remotely sensed images more relevant to the social, political, and economic problems pertinent to land cover and land use change. They draw the conclusion that the

LUCC project and initiatives within the project that involve "socializing the pixel" and "pixelizing the social" offer the potential to achieve the integration, cooperation and collaboration among the natural, social, and remote sensing/GIS science. Another example for the integration of remote sensing and social science present TAUBENBÖCK ET AL. (2009). This study places emphasis on the analysis, whether the physical urban morphology of the city Padang (Indonesia) correlates with socio-economic parameters of its residents. Income and value of poverty are the example indicators of the approach. The authors explore on the capabilities of high-resolution optical IKONOS data to classify patterns of urban morphology based on physical parameters. Moreover, a household survey was conducted in order to investigate on the cities socio-economic morphology. MILLER & SMALL (2003) mentioned a number of further possibilities how data integration permits causal inferences to be made about the underlying dynamics of change in urban environments. For example, by using remote sensing data in conjunction with population and industrial data, the parameter surface temperature can be linked with population density, building type, and urban land use across an urban sector (cf. chapter 3.1). In addition, public health data, e.g. morbidity or hospital admissions, can demonstrate the coherence between remotely sensed urban environmental parameters and various types of environmentally related disease. Last but not least, some disparities in environmental conditions by settlement or section of the urban area can be observed to understand different patterns of vulnerability and environmental stresses.

"If remote sensing data are integrated or used in conjunction with other sources of socio-economic data […] their potential applicability to both research and policy understanding of the urban environment increases significantly" (MILLER & SMALL 2003).

Here, as elsewhere, are great differences between urban areas in more developed and less developed countries in the potential, applicability and need of remote sensing data and the capacity for integration of remote sensing with socio-economic data (MILLER & SMALL 2003). In the majority of cases there are almost no or only incomplete datasets available in the less developed countries. Particularly mega cities in less developed countries like Delhi, Calcutta, Dhaka, Lagos or Cairo (cf. chapter 2.2) are data poor environments. Temporal resolution, coverage and quality of administrative and socio-economic data are insufficient and the knowledge about the living conditions of the residents is correspondingly very limited, incomplete and not up to date.

In contrast to this, the data basis in the more developed countries is much better. Mega cities like Tokyo, New York or Los Angeles are data rich environments, where the integration of remote sensing with other data types is comparably easy to realize and likely to be most fruitful (MILLER & SMALL 2003). In the mega cities of Europe or other more developed regions, the living conditions of its residents are well known. The intra-urban development processes usually take place in a controlled way and are implicated in the urban planning and management. In addition, reliable socio-economic data are collected regularly. For more developed countries already a multitude of examples exist how to link remotely sensed data with socio-economic data. As mentioned above, applications in environmental stresses such as changes in vegetation, air quality and surface temperature as well as traffic monitoring, management and planning can be quoted as examples (MILLER & SMALL 2003, SMALL 2006). The potential for the integration of remote sensing data with socio-economic data in more developed countries lies therefore in advanced disciplines and specific urban applications.

These fields of application theoretically take an important position in less developed countries as well. At the moment, however, the realization is not yet possible since the necessary basis of administrative and other socio-economic data is missing. The prerequisites are completely different in the mega cities of the less developed countries (cf. chapter 2). The processes there usually are uncontrolled and take on an unknown temporal and spatial dimension, so that urban planners are not able to keep the overview. The circumstances are fundamentally more difficult and more complex. Under these conditions it is considerably challenging as well as extensive in terms of costs, time and personnel to conduct a survey or appraisal at regular intervals. Exactly because of this lack of data the potential of remote sensing in developing countries is rather in the derivation of the socio-economic data itself than in the integrative use.

With the task to derive socio-economic data from remote sensing data and thus drawing conclusions on the living conditions in the mega cities of this world, like it is done in this study, the question needs to be answered who will benefit of these investigations and where the demand for such innovative methods will be the greatest.

In mega cities like Delhi, a method of indirect data assessment regarding the living conditions of the inhabitants, which can be applied in a time and cost saving way, is most beneficial. It is for example essential to know about the where and how fast informal structures are developing, in order to determine the place and level of effort to be put into improving the infrastructure to guarantee a sufficient supply of the inhabitants with water, electricity and health services. By means of remote sensing data and with the integration of few socio-economic data a catalogue can be compiled, comprising the living conditions of the inhabitants – and this in a quick, large-scaled, cost effective, by random or regularly repeatable way with a small required data basis. Hence, the lack of in-situ collected socio-economic data can be compensated. In this regard, the most obvious and direct beneficiaries are on the one hand the governmental agencies and urban planners and on the other hand the inhabitants of the affected areas, whose living conditions can be monitored and improved as required. The added value of such a methodology is under the current circumstances of course much greater in less developed than in more developed countries.

3.4 Urban Remote Sensing Today — Interim Conclusion

In summary of the explanation and review of previous as well as current research and development in urban remote sensing, the following conclusions and assumptions can be made for prospective enhancements in this field.

Recent developments in remote sensing in general have an effect on the research, enhancements and application of remote sensing techniques in the analysis of urban environments in special. With the advent of full commercial very high-resolution satellite data, such as QuickBird or IKONOS, new opportunities to capture and map the urban environment become available. Using this data provides the chance to identify recent small-scale land use structures and dynamics at local scale and enables therefore a more detailed characterization of urban areas. Besides an increased amount and quality of remote sensing image data with higher spectral resolution (hyperspectral data) there is as well LIDAR which are together improving the remote investigation of urban environments (HEROLD 2004) (cf. chapter 3.2.1).

But advancing remote sensing technologies do not, per se, lead to improved image analysis results. Sensor improvements and innovative image data need rather to be adequately explored through adapted image analysis approaches. Hence, the progress in Earth observation data was accompanied by the development of new and innovative image analysis methods at the same time which today are also of particular importance for the research of urban areas (HOSTERT 2007). Several approved remote sensing techniques have already shown their value in mapping urban areas and have been successfully used as data sources for the analysis and modeling of urban growth and land use change. Nevertheless, there is still a need for improved methods and the consideration of new concepts. Especially, in the case of classifying complex urban environments with VHR remote sensing data, the "classic" pixel-based approach is not suitable any more. Hence, in order to obtain more accurate and detailed remote sensing products, the introduction of concepts in object-based analysis of spatial pattern and structures, providing second order image information, has evolved into a veritable alternative (DARWISH ET AL. 2003, HEROLD 2004, HURSKAINEN & PELIKKA 2004 and SLIUZAS ET AL. 2008a) (cf. chapter 3.2.2).

One of the most important findings of the above review is that the contribution of remote sensing to urban planning and management goes beyond mapping the objects of the built environment alone (SLIUZAS 2008). Remote sensing scientists are rather for instance able to monitor and forecast urban residential expansion, to describe urban change, and to provide uniquely useful information for social research (RINDFUSS & STERN 1998). The physical appearance in urban environments is a reflection of human activity. An isolated examination of social questions detached from geospatial questions does neither meet the requirements of social science nor the requirements of remote sensing. Thus, urban remote sensing has the potential to be an important meeting point for social and physical scientists (cf. chapter 3.3). Today, the urban remote sensing community is just at the beginning of integrative work, the researchers are here in the early stages of development.

Recent investigations make use of well established, classic methods and algorithms which were originally applied to environmental applications such as vegetation mapping or mapping of impervious surface. But using these methods will not suffice to do justice to the demands and requirements of urban questions. Hence, primarily considering recent global developments and urbanization processes, progress in further development of analysis methods is absolutely required and essential. Improved methodologies and innovations in this research field will arouse public interest and even produce interest by skeptical social scientists and urban managers. For instance, in the field of disaster management and prediction this has already happened. Only by the availability of robust and fully developed methods social scientist, but also urban planners and managers, will make use of remote sensing derived products in their day-to-day business.

Since we have not reached this phase yet, research in this field of remote sensing applications still needs to consolidate user’s interest. This describes the current status which forms at the same time the baseline for the objectives and investigations presented in this thesis. The major task within this research is now the combined application of remotely sensed imagery and socio-economic data for mapping, capturing and characterizing the socio-economic structures and dynamics within the mega city of Delhi.

Chapter 4

The Study Area Delhi, India

The rapid urbanization process experienced by the majority of developing countries during the last few decades — described in chapter 2 — has also reached India. Since the country's independence from Great Britain in 1947 the present urbanization process in India has developed at an enormous pace (Krafft et al. 2003). While in 1951 about 17 percent of India's inhabitants where living in urban agglomerations, in 1981 about 23 percent and already in 2013, about 32 percent were city dwellers (cf. Figure 4-1) (Census Operations 2001, World Bank 2015/Url 23).

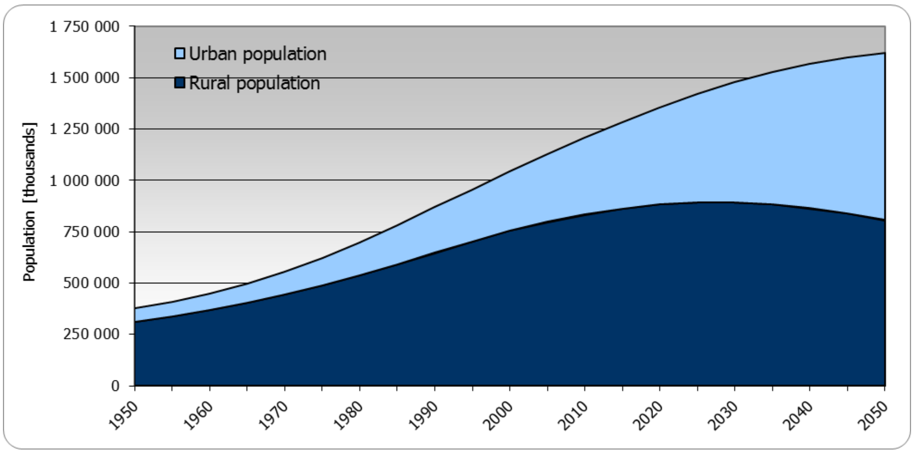

Figure 4-1: Population growth in India: 1950 – 2050. The total population of India results from the sum of the urban and rural population amount *(Data sources: Haub 2002, UN World Population Prospects: The 2006, 2007 and 2014 Revision)*.

As shown in Table 4-1, for the year 2005, 29 percent or about 326 million people were registered in urban settlements of India. It is expected that in the year 2040 almost 50 percent of the Indian people will be counted among the urban population (cf. Figure 4-1).

ZERAH (2000) already predicts this event for 2020. Comparative data from other countries as well as from the categories of more developed and less developed regions can be found in Table 4-1. Nevertheless, the Indian subcontinent is still strongly affected by rural structures.

Table 4-1: Population data of India and selective comparative data

				Urban population						
Country	Total population [thousands] 2005	Land area [km²] 2005	Urban settlements [% of land area] 2000	Number of urban dwellers [thousands] 2005	As percentage of total population 2005	Average annual growth rate [%] 2000-2005	Density [per km² of urban extent] 2005	Percentage living in slums 2005	Percentage with access to improved sanitation 2004	Percentage with access to improved water source 2004
World	6 514 751	129 830 789	2.7	3 164 635	49	2.1	902	…	80	95
More developed regions [a]	1 215 636	49 068 852	3.8	899 848	74	0.6	482	…	98	100
Less developed regions [b]	5 299 115	80 761 937	2.0	2 264 787	43	2.7	1 381	37	73	92
INDIA	**1 134 403**	**2 973 190**	**6.9**	**325 563**	**29**	**2.4**	**1 592**	**35**	**59**	**95**
Selective comparative data										
Angola	16 095	1 246 700	0.1	8 684	54	4.8	8 469	86	56	75
Egypt	72 850	995 450	2.4	31 062	43	1.8	1 298	17	86	99
Nigeria	141 356	910 770	1.6	65 270	46	4.1	4 390	66	53	67
China	1 312 979	9 326 410	2.9	530 659	40	3.1	1 936	38	69	93
Bangladesh	153 281	130 170	7.8	39 351	26	3.6	3 863	71	51	82
Philippines	84 566	298 170	2.9	53 032	63	3.5	6 170	44	80	87
Turkey	72 970	769 630	5.7	49 097	67	2.1	1 119	16	96	98
Russian Federation	143 953	16 381 390	1.1	104 985	73	-0.6	563	…	100	100
Germany	82 652	348 770	17.3	60 630	73	0.2	1 006	…	100	100
Sweden	9 038	410 330	8.7	7 621	84	0.5	212	…	100	100
Portugal	10 528	91 500	14.0	6 066	58	1.7	473	…	…	…
Brazil	186 831	8 459 420	2.2	157 369	84	2.1	835	29	83	96
Mexico	104 266	1 908 690	5.3	79 564	76	1.3	780	18	91	100
Haiti	9 296	27 560	1.7	3 974	43	5.3	8 501	…	57	52
United States of America	299 846	9 161 920	8.2	242 236	81	1.4	321	…	100	100
New Zealand	4 097	267 990	3.0	3 532	86	1.3	437	…	…	100

[a] More developed regions comprise all regions of Europe, Northern America, Australia/New Zealand and japan. The term "developed countries" is used to designate countries in the more developed regions.
[b] Less developed regions comprise all regions of Africa, Asia (excluding japan), Latin America and the Caribbean plus Melanesia, Micronesia and Polynesia. The term "developing countries" is used to designate countries in the less developed regions. The group of least developed countries is included in the less developed regions.

Data source: UN Urban Population, Development and the Environment 2007

Altogether, more than 1.13 billion people are residents of the second most populous country of the World. At the same time, India is with 381.54 Pop./km² (2005, cf. Table 4-1, after UN 2008a) one of the most densely populated states of the world, whereas the density varies regionally very strongly (from metropolitan areas with partly > 6,000 Pop./km² to the peripheral mountain and desert regions with < 100 Pop./km²). In comparison with this, Germany has a population density of 230.35 Pop./km² (URL 8).

As of the beginning of the 21st century, India has 35 cities with more than one million people are living in (KRAFFT ET AL. 2003). Thereof, three mega cities — Mumbai, Kolkata and Delhi — have a population size that has even exceeded the 10 million threshold (cf. Table 2-2 in chapter 2) (AHUJA 2006). Together, about 40 million people are living in these mega cities, which is comparable with half of Germany's total population. Moreover, these mega cities are ranking under the top ten of the most populous cities of the world (cf. Table 2-2, UNITED NATIONS 2004). Consequently, in a global comparison, India is leading the statistics. According to that, the growth of the large urban agglomerations in India proceeds by a multiple more quickly than the growth of the small towns and medium-sized towns. Hence, metropolises are subject to the major proportion of urbanization dynamics and are therefore particularly affected by the resulting infrastructural problems (see also chapter 2). Meanwhile, between a third and the half of the inhabitants of India's mega cities are living in informal settlements (KRAFFT 1996).

Despite the considerable migration from rural to urban areas, one cannot talk about an extensive rural exodus in India. Well-known push- and pull-factors play an important role, but even more the city-internal natural increase in population is responsible for the rapid growth of the large urban agglomerations. This development is evoked by a decreasing mortality rate combined with a constantly high birth rate as described for numerous countries of the developing and newly industrializing countries (KRAFFT 1996 & SELBACH 2009).

In order to comprehend Delhi's present situation and the corresponding living conditions of its residents, the following chapter 4.1 overviews the urban development, the population growth as well as the resulting implications. In chapter 4.2 the chosen test sites within Delhi are presented and the motivation for their selection is explained.

4.1 Introduction into the Study Area: Urban Development, Population Growth in Delhi and Resulting Implications

The city of Delhi looks back on a changeful history of more than three millenniums (KRAFFT 1996, MANN 2006, PECK 2005, STROBEL 1997 & SELBACH 2009). "Changing dynasties and ever new ruling elites have over the centuries attempted to demonstrate their leadership by restructuring and rebuilding the city in its outlay and architecture" (KRAFFT 1996). Starting as the residence town of the Moghal, then developed to a provincial town in the colonial empire British-India and was constituted to be the imperial residence, and finally Delhi became the capital city of the Indian Union. Thus, Delhi was subjected to a permanent process of change accompanied by dramatic deformations (GUPTA 2006, MANN 2006 & STROBEL 1997).

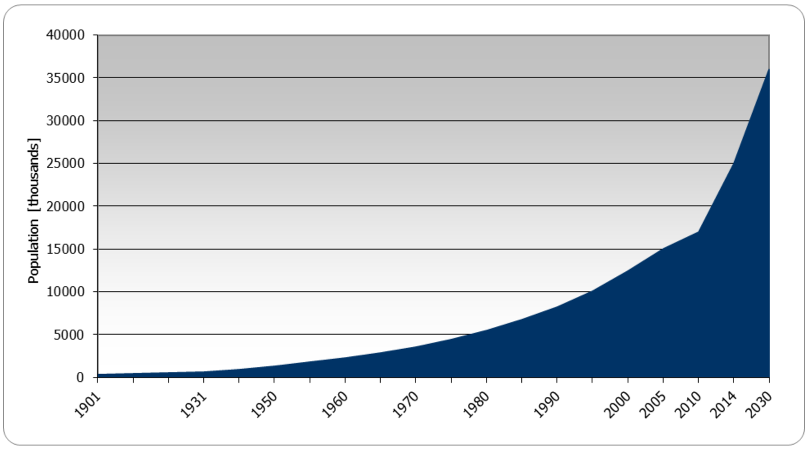

Figure 4-2: Population growth of the urban agglomeration Delhi, India: 1901 – 2030 *(Data sources: UN World Population Prospects: The 2006, 2007 & 2014 Revision and HAUB 2002).*

In 1901 Delhi was a town with only 0.4 million inhabitants. Delhi's population started increasing after it was named as the capital of British India in 1911 (BATRA 2005, STROBEL

1997). The decisive phase for the development of today's dimension of the urban population in the history of Delhi was the time after India's declaration of independence in 1947. Directly after the country's independence from Great Britain, the city of Delhi underwent an extensive change (cf. Figure 4-2). Between 1950 and 1955 Delhi recorded an annually population growth of about 5.26 percent. Until the end of the 1990ies the growth rate continued on a high level between 3.9 and 4.5 percent annually (cf. Table 4-2) (Un 2007).

Already in the 1970ies about four million people were living in the city of Delhi. In the end of the 1980ies the number of inhabitants passed the eight million threshold, and in 2005, only 60 years after the independency, over 15 million people were surveyed over an area of 1,483 km², making it one of the world's most densely populated cities (cf. Figure 4-2) (Sliuzas et al. 2008a & Un 2007). The population density in the Delhi area averages 9,500 [Pop./km²], but can reach as high as 150,000 [Pop./km²] locally (Sliuzas et al. 2008a). This study shows in chapter 8.1 that even a population density of 250,000 [Pop./km²] and more can be observed in Delhi's informal settlements. Within only few decades, Delhi could therefore increase its population tenfold, an increase that took, for comparison, in New York more than 150 years (Kröhnert 2003). Today, Delhi is a steadily growing mega city. According to Un-Habitat (2003a) the growth rate was predicted to drop to a relatively moderate rate below two percent per annum until 2010 whereas in contradiction to the forecast the growth rate rose to 3.17 percent in 2014 already (Un 2014) (cf. Table 4-2). For 2030, a tremendous growth to 36 million inhabitants (Un 2014) is expected (cf. Table 2-4 in chapter 2.2).

Facts about Delhi

- National Capitol Region (NCR) of Delhi covers an area of about 33,578 km²;
- NCR surrounds and includes the city/state of Delhi, formally known as the National Capitol Territory (NCT) of Delhi, it also covers parts of the neighboring states;
- NCT is situated on 28°30′N latitudes and 77°00′E longitude, maximum length is almost 52 km, greatest width is about 48.5 km, covers an area of 1,483 km², altitude between 213 and 305 m;
- Yamuna river and terminal part of the Aravali hill range are the main geographical features;
- NCR accommodated a population of more than 37 million people (2001), of which about 15 million lived in Delhi alone;
- Population density in the NCT averages 9,500 [Pop./km²].

(BATRA 2005, MAHIR 2005, NETZBAND ET AL. 2005, UN 2007)

Not only Delhi's population has increased exponentially, but also Delhi's area has grown in a similar extent since India's independence. The municipal area outreaches today far beyond the borders of Old and New Delhi. The number of inhabitants refers therefore since 1961 to the area of the former province Delhi, which was converted to the National Capital Territory (NCT) in 1992 and holds since then the status of a federal state. Within the NCT the urbanized areas captured approximately 60 percent of the area of the federal state in the beginning of the 21st century, while 40 percent were still classified as rural areas. The urbanized area increased fivefold within half a century (1941-2001) and fifteen fold since the appointment as capital (Köberlein 2003, Mistelbacher 2005 & Selbach 2009) (cf. blue box on this page). With the rapid speed of urbanization the rural area of Delhi has shrunk simultaneously. The number of rural villages has declined from more than 300 in the beginning of the 20th century to 165 in 2001. Hence, the percentage of rural population of Delhi has decreased from about 47 percent in 1901 to merely 7 percent in 2001 (BATRA 2005 & URL 9). According to that, about 90 percent of the population of the NCT is nowadays living in the *Urban Agglomeration of Delhi*.

Table 4-2: Delhi's annual growth rate between 1950 and 2030

Time period	Average annual rate of change [%]
1950 -1955	5.26
1955 - 1960	4.96
1960 - 1965	4.40
1965 - 1970	4.32
1970 - 1975	4.52
1975 - 1980	4.56
1980 - 1985	5.52
1985 - 1990	5.67
1990 - 1995	4.87
1995 - 2000	4.75
2000 - 2005	3.42
2005 - 2010	3.22
2010 - 2015	3.17
2015 - 2020	2.65*
2020 - 2025	2.18*
2025 - 2030	1.94*

*forecast data
Data sources: UN World Urbanization Prospects: The 2014 Revision

Numerous causes can be listed for the rapid growth of Delhi. As described for Indian mega cities in general, several push- and pull-factors play an important role (see introduction of chapter 4). On the one hand, the high population pressure and the poor living conditions in the rural areas surrounding Delhi (e.g., in the federal states of Haryana, Rajasthan and the most populous state Uttar Pradesh) drive people to move into the city (DUPONT 2000). On the other hand, Delhi is the seat of government and, with vibrant trade and excellent employment opportunities, the industrial center of Northern India. Both are decisive reasons, why Delhi used to be so attractive for immigrants in the past and today still is (BATRA 2005, MANN 2006 & SELBACH 2009). In addition to that, there is a significantly natural increase in population, which is mainly generated by a higher life expectancy.

The continuous stream of immigrants and even the rapid growth of population in itself have increased the pressure on the existing infrastructure. Hence, the rapid growth of the urban agglomeration posed great difficulties to the urban planning and management, which used to be generally well organized till 1947. The extensive effect on the development within the NCT is explained in more detail in the following.

The creation of new settlements did basically not happen with a profound urbanistic development concept. "On the spot decisions" were rather predominant compared to systematic planning (GUPTA 2006). Only in the year 1955, when the government was obliged to put an end to the unplanned growth of the city, because of a severe cholera epidemic, the *Delhi Development Act* was passed. In the following (1957) the *Delhi Development Authority (DDA)* was founded with the task to design an urban development strategy *(Delhi Master Plan)* for the coming decades (GUPTA 2000 and 2006, MANN 2006 & STROBEL 1997). Subsequently, the DDA has become the central and most important development authority of the city of Delhi (SELBACH 2009). For more details concerning the DDA and its functions as well as the contents of the different master plans generated over the years, see KÖBERLEIN (2003).

The concept of the DDA could however only be implemented partially because the imposed objectives could not bear the continuously high population growth. The urban resettlement and residential construction programs failed since the DDA was not able to close the supply gap on the municipal residential market. Therefore, the deficit of living space could never be covered sufficiently. Primarily for the low-income population sufficient living space could not be provided. One of the major problems concerning the effective realization of the urbanistic concepts and development plans is the fact, that decision-makers generally have not been in the past and today still are no city planners but politicians (KÖBERLEIN 2003 & SELBACH 2009). "…this has resulted in rapid expansion of constructed areas at a very fast pace almost beyond the control of the authorities entrusted with planning and development actions and regulation of the city workers" (SARMA ET AL. 2003). Quoting KÖBERLEIN (2003) the situation of Delhi's urban development can even be called a dilemma, for which "scheming politicians and money grabbing racketeers" have to take the responsibility.

The politicization and bureaucratization of the city planning has led to an unbalanced development within the urbanistic planning zones of Delhi and hence to the development and establishment of a diversity of settlement structures. That means, besides the exponential growth of the population and the size of the urban area, the governmental planning authorities are also responsible for the high level of heterogeneity in the city structure (MANN 2006 & SELBACH 2009).

Hence, due to this enormous growth, Delhi is affected by a high degree of fragmentation between planned urban upper class quarters and informal settlements (*Jhuggi Jhompri* clusters) within nearby quarters. Besides the historic quarters of Old Delhi (the oriental Old Town) (EHLERS ET AL. 1993) and New Delhi (the colonial New Town), several different settlement types have developed and established in Delhi's municipal area over the past 60 years. All these types vary in their status of legality as well as in the socio-economic situation of their residents. In the following, the different settlement types that can be distinguished in Delhi are listed:

- Gated Communities,

- Government Quarters,
- Resettlement Colonies,
- Unauthorized Colonies [7],
- JJ[8]-Colonies as well as
- Urban villages.

To get a general idea, Table 4-3 comprehends some explanations according to the development of the settlement types, their main characteristics and the socio-economic circumstances of their dwellers.

Compared to this list of settlement types, BATRA (2005) described a total of nine different settlement types for Delhi. He distinguishes the following types: (1) planned/ approved colonies, (2) regularized unauthorized colonies, (3) resettlements/relocated colonies, (4) urban villages, (5) unauthorized colonies, (6) notified slums, (7) JJ clusters, (8) rural villages and (9) pavement dwellers. Most of these settlement types (no. 2 and 4-9) are considered as informal. The author also gives population estimates, whereas in 2001 almost five million people (approximately 35 percent of Delhi's population) were living in notified slums, JJ clusters and on pavements. In this study, these three types are not listed separately, but are summarized in the term "JJ-Colonies" (cf. Table 4-3). Since the JJ-Colonies are the slums of the city of Delhi, in turn, as described in chapter 2.4, this perception will be used interchangeably and together in this context with the term "informal settlements".

It is important to note, that not only the slums of Delhi developed informally. Also the unauthorized colonies were built without permission and they are partly not connected to technical and social infrastructure (cf. Table 4-3). However, in this methodology the unauthorized colonies (e.g., *Tughlakabad Extension, Sainik Farms*) are not assigned to the category "informal settlement" since the structures are mostly planned and the living conditions are better or even much better than in the slum areas of Delhi. The majority of the inhabitants belong to the upper class and lower middle-class. Only a small percentage belongs to the upper lower class. In comparison to BATRA (2005), in this paper also the settlement type "urban village" is not classified as informal. In fact, urban villages score high in the deprivation index and they are vulnerable residential areas, but the majority of the residents can be numbered to the middle and upper middle class of Delhi. This classification also corresponds with the local expert knowledge as well as with interview data of local

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[7] There are very different expressions of this settlement type. Details of the development and growth of Delhi's unauthorized colonies can be found in BOSE (1980).

[8] In India slum related residential areas are characterized as JJ-colonies. JJ stand for *Jhuggi Jhompri* and means in Hindi "hut dwelling" (MANN 2006).

inhabitants conducted in the respective areas (cf. chapter 5.2). These examples point up that in a city itself different possibilities of categorization, assignment and definition of settlement types appear. A direct comparison of these studies (and numbers) is therefore relatively difficult and can, (if at all), be carried out only after an exact sighting of the respective definitions.

These examples clarify that there are different possibilities of the categorization, assignment and definition of settlement types even within a single city. Therefore, a direct comparison of these studies is relatively difficult and can, if at all, be carried out only after an exact analysis of the respective definitions and numbers. Nevertheless, both categorizations show, even if they are partly different, that the settlement structure in Delhi is very heterogeneous and an allocation can be difficult.

Summarizing one can say that besides the intended functional separation of living, working, supplying and traffic constituted in the master plan, in particular the internal, socio-economic differentiation of the residential areas has evoked a heterogeneous development within the urban agglomeration of the NCT (SELBACH 2009). Primarily the South of Delhi is largely inhabited by the middle and upper class, while the northern and eastern areas are populated by the poorer sections of the population. Hence, in Delhi a significant socio-economic gap from South to North is observed (MISTELBACHER 2005) (cf. Figure 4-3).

The disparities on the "total-municipal" level of Delhi are also existing on a small scale, this means at a local level. Planned and unplanned, wealthy and poor as well as formal and informal quarters are located very closely at a small scale and they partly merge seemingly seamlessly (SELBACH 2009). Thus, this very heterogeneous and highly complex urban structure in itself gives a clear indication of the very different infrastructural supply of the inhabitants. This also concerns primarily the water supply and disposal of waste water, which is examined particularly in this study (PARAI ET AL. 1994).

Especially in the JJ-Colonies, which, besides the unauthorized colonies, strongly shape and dominate Delhi's cityscape, the situation of the population is very difficult and the preconditions for an improved workaday life are bad. Because of this, this settlement type was included in the examinations and became a focal point of this study.

Table 4-3: Summary of the different settlement types in Delhi: development, characteristics, legal status and the socio-economic status of their inhabitants

Settlement type	Development	Characteristics	Residents
Gated Communities	• (a) In the 1970 and 1980ies by private builders individually constructed residential areas (e.g. Greater Kailash II),	• (a) mostly single-story to three-story bungalows, but also (b) compact apartment buildings within bigger housing estates in the urban outskirts (block by block buildings),	• Quarters of the upper middle class and upper class
e.g. Greater Kailash II, Vasundara Enclave	• (b) Since the 1990ies constructed by housing societies or sometimes by the DDA (e.g. Vasundara Enclave),	• Individual blocks are fenced off in many cases or are open to the public only during the day,	
	• Dominate primarily in southern Delhi,	• For Indian conditions generous, individually constructed residential areas	
	• Authorized		
Government Quarters	• Municipal house building by the DDA,	• At first in two-story style, four- to six-story later on, yellow painted,	• Housing space for the employees in the public service
e.g. Kalkaji DDA flats, Narmada Apartments	• Construction of the housing estates was carried out very generously and always around a park located in the middle,	• depending on the size of the individual accomodation units (2, 3 or 4 rooms) one distinguishes apartment buildings in Type II, III, IV Government or DDA flat,	
	• Complexes built fast and economically,	• Simple design,	
	• Authorized	• Apartment buildings often are in structural bad condition; neglected basic structure of buildings	
Resettlement Colonies	• Planned and built by the Indian state,	• Single properties are situated in rows right next to each other	• Very different living conditions can be observed: from slum similar conditions up to infrastructural circumstances of the lower and middle middle-class
e.g. Trilokpuri, Dakshinpuri, Madangir Camp;	• Enforced clearance/relocation of the intra-urban JJ-Colonies[1],	• Planned, but also very dense building density	
	• Peak of development: *slum clearances*[1],	• Since the base area of the individual plots is very small, the owners of the houses built up one or more additional story illegally	
	• Usually located at the periphery of the city	• Poor housing conditions, overcrowding and are mostly unattractive due to the distance to possible imlovment	
Unauthorized Colonies	• Settlements developed informally,	• Mostly planned structures (column- respectively block-parcelling), but not connected to technical and social infrastructure,	• Cover the complete socio-economic spectrum: vary from the upper class[2] to the lower middle-class and upper lower class
e.g. Sainik Farms[2,] Tughlakabad Extension	• Inhabitants purchase parcel of land by landowners or by *clandastine colonisers* (illegality of the subdivision). The plot holders cannot get a permission to build. Thus, the construction are carried out without the compliance of the design specifications	• Structure of the quarters varies with the socio-economic status of their residents from very dense and multi-storied in structurally acceptable, partly luxury conditions over dense and in simple style up to settlements which externally are not different	
		• Infrastructural environment of the colonies varies according to the socio-economic status	
JJ-Colonies	• Settlements developed informally,	• Are located along the tracks, river banks, open drains and on the outskirts, but also on pavements (in the middle of the city),	• Are the slums of the city of Delhi,
e.g. Bhomiheen Camp	• The acquisition of land is spontaneously and without payment (= illegal occupation of land, the inhabitants do not have any tenure)	• Spread out over the whole municipal area in larger and smaller units,	• Lower class
		• Strong variance in the settlement size: smallest JJs comprehend only a few huts (slum pockets), but they can, as marginal quarters, comprehend about 10,000 accommodation units,	
		• They are built in the simplest style (temporary shelters out of corrugated metal sheet or plastic tarpaulins) up to houses built from clay bricks in the marginal quarters,	
		• Very high housing density, • As a result of the status without rights a supply with technical or social infrastructure is not existent, informal channels of supply are practiced,	
		• Very bad living conditions, lack of basic services (e.g. water, sanitation)	
Urban villages	• Urbanized villages, which were enclosed as a result of the urban growth,	• Irregular, from dense up to very dense structure with a complex road and path network	• Middle to lower class
e.g. Mehrauli	• Very different development[3],		
	• Legal exceptional position: independent settlements, which are not subject to the building laws and construction specifications of the DDA		

Sources: BANERJEE 2002, BOSE 1980, DUPONT 2000, GI & GNCT 2001, MANN 2006, MEHRA 2005, MENON 2000, SELBACH 2009, SONI 2000, TARLO 2000

[1] The development of the resettlement colonies took place in several phases: The governmental relocation of a large number of people started in the 1960ies with the resettlement of the refugee camps and the slum quarters. Many new settlements in the outskirts were built and extended. The clearing of the slum areas culminated in the "slum clearance" actions from 1975 to 1977 where approximately 700,000 slum dwellers were resettled by force (MANN 2006).

[2] *Sainik Farms* farm houses: Members of the upper class quarters live illegally in luxury villas in the "farm belt" outside the densely populated areas of Delhi. The villas are surrounded by big parks and gardens, and are protected by high walls or fences. Although the residents are no more farmers, they are allowed, due to their status, to produce groundwater.

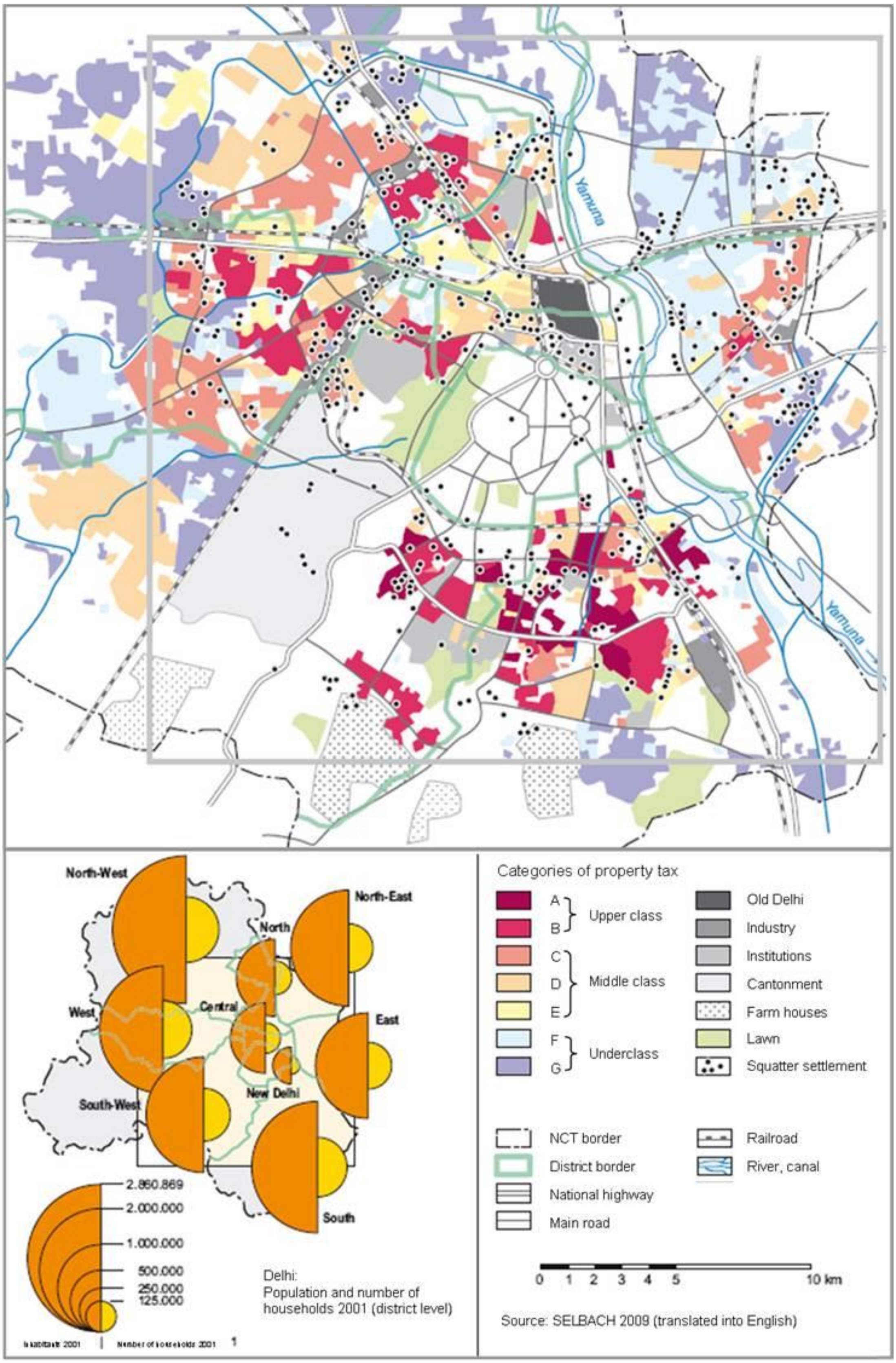
[3] Since 1911, 135 of the 150 urban villages within the new founded province of Delhi have been swallowed by the steadily growing city (GNCT 2008). The development of the urban villages in Delhi took place in very different ways: On the one hand, numerous villages have suffered and are today still suffering of an economical and in the following as well of a social degradation process, evoked by the loss of the economic basis, which is traditional agriculture and allied occupations. These villages hence are on a social decline, drifting towards the informal sector. On the other hand, some villages (c.f. Mehrauli) are of interest from a historical point of view. Here a gentrification process and hence a positive trend can be observed (MEHRA 2005).

Already in the middle of the 1990ies about 35 to 50 percent of Delhi's population lived in slums or slum similar settlements (JAIN 1990, KRAFFT 1996, STROBEL 1997). In the literature very different information on the actual number of slum residents in Delhi exists. The numbers vary from 1.6 million (DUPONT 2006) to three million (HAIDER 2000) and four million (ASHA 2008) up to almost five million (BATRA 2005). After SINGH ET AL. (2007) even "about 50 percent of the population is living in informal settlements" and is plagued with inadequate infrastructural facilities and a number of water and waste water related problems (NIEBERGALL ET AL. 2009). This number includes as well a part of the inhabitants of the unauthorized and resettlement colonies and in addition to that partly inhabitants of the urban villages, which show slum similar conditions due to their disadvantageous development. Quoting DUPONT (2000) the number of individual Jhuggi Jhompri clusters has increased from approximately 100,000 to 500,000 between 1981 and 1994. Although there are no more governmental resettlement programs today, the slum dwellers are threatened by eviction and displacement every day since they are deprived of all rights (SELBACH 2009).

As described for informal settlements in general (cf. chapter 2.4), the JJ-Colonies and some other slum similar areas in Delhi also combine various negative features. They are characterized by an insecure residential status, insufficient access to safe water and sanitation as well as an inadequate or even inexistent infrastructure of power, traffic, health and education. Moreover, poor structural quality of housing and overcrowding is observed. The situation of water supply in the informal settlements and other settlement types of Delhi is described in detail by SELBACH (2009), while the disposal of waste water is specified well by SINGH (2008).

All these slum characteristics become directly and indirectly apparent within the settlement structure of the city. The same applies as well to almost all other settlement types of Delhi. Also their features are reflected in the settlement structure and therefore they can be distinguished on the basis of their different physical entity. Vice versa, the potential of remote sensing is restricted to the detection and analysis of "visible" characteristics of the urban environment. Hence, the outward appearance is important to identify different settlement types and therefore different living conditions using remote sensing data and analysis methods.

A more detailed specification of the physical parameter values of the different settlement types can be seen in Appendix A.6.



Source: SELBACH 2009 (translated into English)

Figure 4-3: Socio-economic disparities within the municipal area of Delhi, India *(Source: SELBACH 2009 after CENSUS OF INDIA 2001/URL 9, DUPONT 2000, EICHER 2006 & MISTELBACHER 2005)*.

4.2 The Selection of Useful Test Sites within Delhi

Within the NCT of Delhi based on prior knowledge of the local conditions, a comprehensive literature review and the support of pre-studies carried out by R. Singh and T. Krafft on Delhi several test areas with different locational, social and settlement structures were selected. To best capture the heterogeneous nature of Delhi three different test areas are used to cover different parts of the urban agglomeration. The locations of the test areas within Delhi are shown in Map 4-1 (see introduction of chapter 4). The specific pre-selection of the test areas is based on the following arguments:

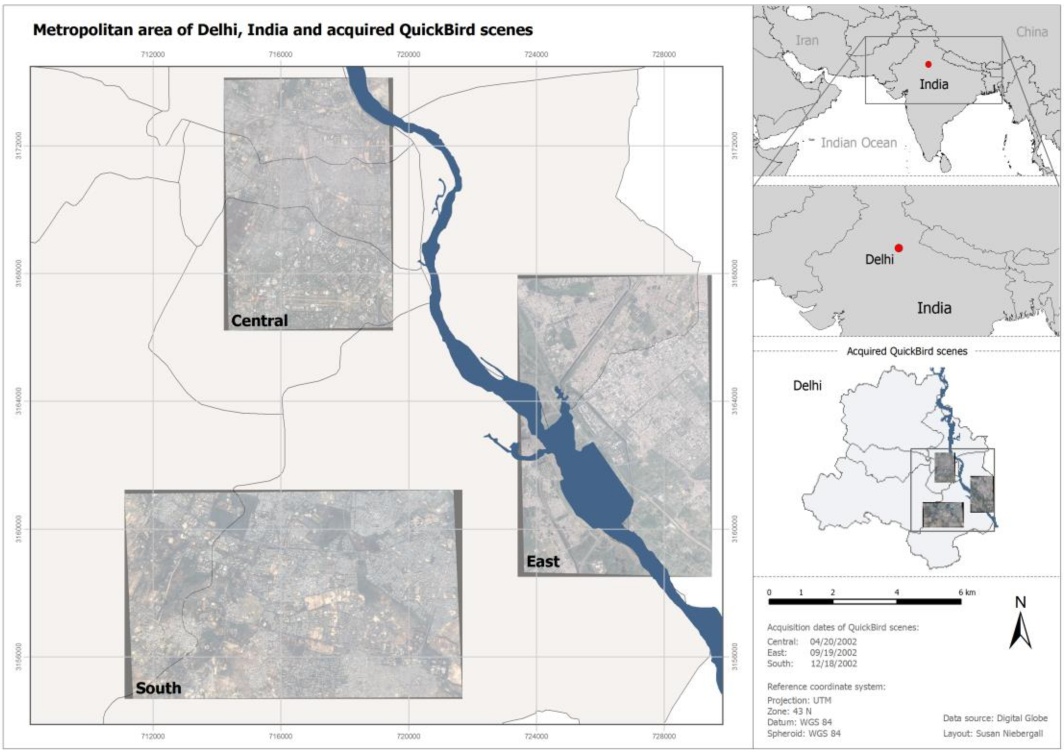
- Central Delhi (C) represents complex urban development evident in its mixed land use, co-existence of high rise and JJ-Colonies at very close quarters. The historical centre of Delhi is an important and interesting area for investigation, since it is on the one hand the oldest preserved part of the city (walled city *Old Delhi*) ailing with ageing structural and infrastructural problems (*downgrading* process) since many years. On the other hand, Central Delhi shows with the government quarter probably the best supplied district of the city.

- The south of Delhi (South Delhi — S) is of special interest since this area has developed extremely heterogeneously and shows great differences with respect to infrastructural conditions within nearby quarters. This fact is particularly of importance for the evaluation of remote sensing data and therefore for this study. Moreover, South Delhi is more disadvantageous in terms of water availability due to its location at the tail end of the water provision system. This area represents the fringe of the city, dotted with urban villages also experiencing ground water depletion and contamination problems.

- The eastern part of Delhi (*Trans-Yamuna* area) has just like the southern part developed very heterogeneously and hence great infrastructural differences become apparent. The Trans-Yamuna area is experiencing mushrooming of lower and lower middle class housing complexes. This part of Delhi is, moreover, the district with the strongest sewage problems.

Following the pre-selection of the three test areas and thus of the QuickBird images (a detailed description of the acquired satellite data and the QuickBird sensor is given in chapter 5.1), the final selection of common test sites was performed. A finer respectively a more focused selection was necessary, since an investigation of all three test areas (in total almost 170 km²) and in particular of all inhabitants of these areas was not applicable by reason of limited human and financial resources and the high expenditure of time required.

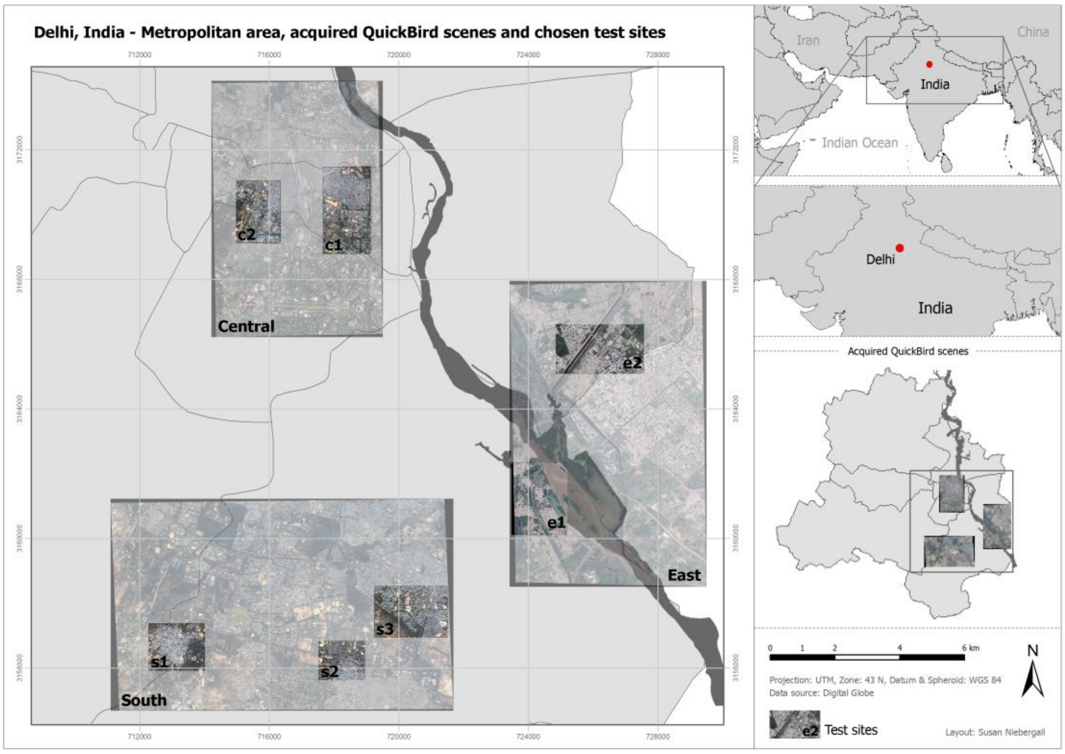
The unplanned rapid expansion and the emerging spatial fragmentation in Delhi result in increasing "social gradients", so that not only the social differences are continuously getting stronger but also the visible contrasts of the urban structure (NIEBERGALL ET AL. 2009). Since the appearance of different urban structures on-site as well as in the satellite images is a key issue of this thesis, especially this fact was taken into consideration during the selection of the test sites.



Map 4-1: Area of investigation: Metropolitan area of Delhi, India and acquired QuickBird scenes.

Against this background a total of seven single test sites were chosen. The selection was following a gradient approach, i.e. selection of particularly those areas, in which structurally highly different residential areas are situated in direct vicinity, while specific care was taken to include various types and gradients of residential areas (cf. chapter 4.1). During the selection specific attention was also paid to further factors, such as the geo-location of water- and waste water-related infrastructure such as canals, water and sewer pipes, open drains, etc. Moreover, all settlement types occurring in Delhi (cf. Table 4-3) shall be covered by the selection of the test sites. Hence, the test sites show a high socio-economic gradient and large visible contrasts within short distances.

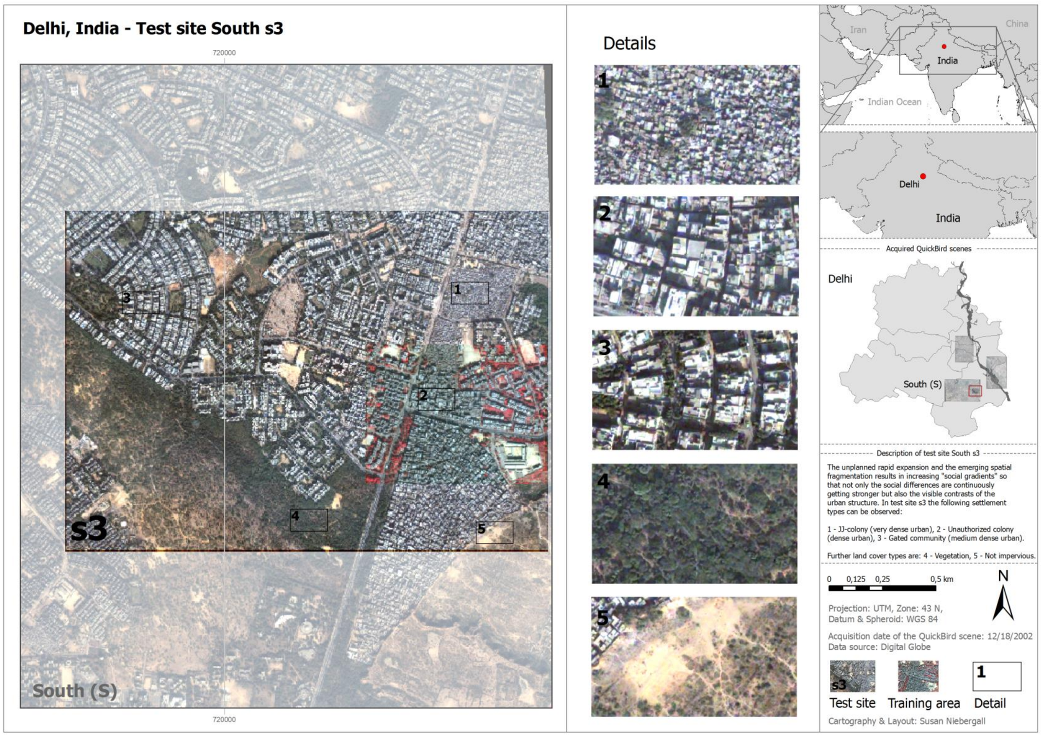
Primarily in two of the seven test sites — in test site s3 and s2 (cf. Map 4-2, Map 4-3, and Map 4-4) — elaborate remote sensing image processing was done. As described in the determination of the pre-selection of the three test areas (see chapter 4.2), South Delhi has developed extremely heterogeneously and shows great differences with respect to infrastructural conditions within nearby quarters. Especially within test site s2 and s3 the visible as well as social contrasts are strongly pronounced. Besides that, taking both test sites together, all settlement types are represented which forms a good basis for this investigation. Moreover, South Delhi represents an area, disadvantageous in terms of water availability and water quality, which is a main concern of the research initiative.



Map 4-2: Acquired QuickBird scene South (s) and chosen test sites s1, s2 and s3 (for an enlarged map cf. Appendix, A.3).

Within test site s3, moreover, a training area was selected in order to test the data analysis steps at a first stage at this area (cf. Map 4-3). The developed methodology was then transferred to the whole test site s3 and the transfer site s2 correspondingly (cf. Map 4-4). Like both test sites, the chosen training area also shows several forms of settlement structures. Besides middle class residential districts like the *Alaknanda* apartment complexes and the *Kalkaji DDA flats*, unauthorized colonies of the lower middle class and upper lower class like *Tughlakabad Extension* as well as settlements of the poorer lower class like the JJ-Colony *Bhomiheen Camp* are situated within this area (cf. Appendix, A.6). A similar approach chose LO (1995) and HARVEY (2002a, b), who tested population models in another study area but within the same remotely sensed image. As in the work being available here, in their studies, an image is divided into two parts: one part for model development and the other part for model validation (WU & MURRAY 2007).

In comparison to the remote sensing image processing, a household survey selecting samples from various kinds of residential areas, including respondents from various socio-economic groups, was carried out in all seven test sites (cf. chapter 5.2). Moreover, a comprehensive field survey was conducted in the same areas (cf. chapter 5.3).



Description of test site South s3

The unplanned rapid expansion and the emerging spatial fragmentation results in increasing "social gradients" so that not only the social differences are continuously getting stronger but also the visible contrasts of the urban structure. In test site s3 the following settlement types can be observed:

1 - JJ-colony (very dense urban), 2 - Unauthorized colony (dense urban), 3 - Gated community (medium dense urban).

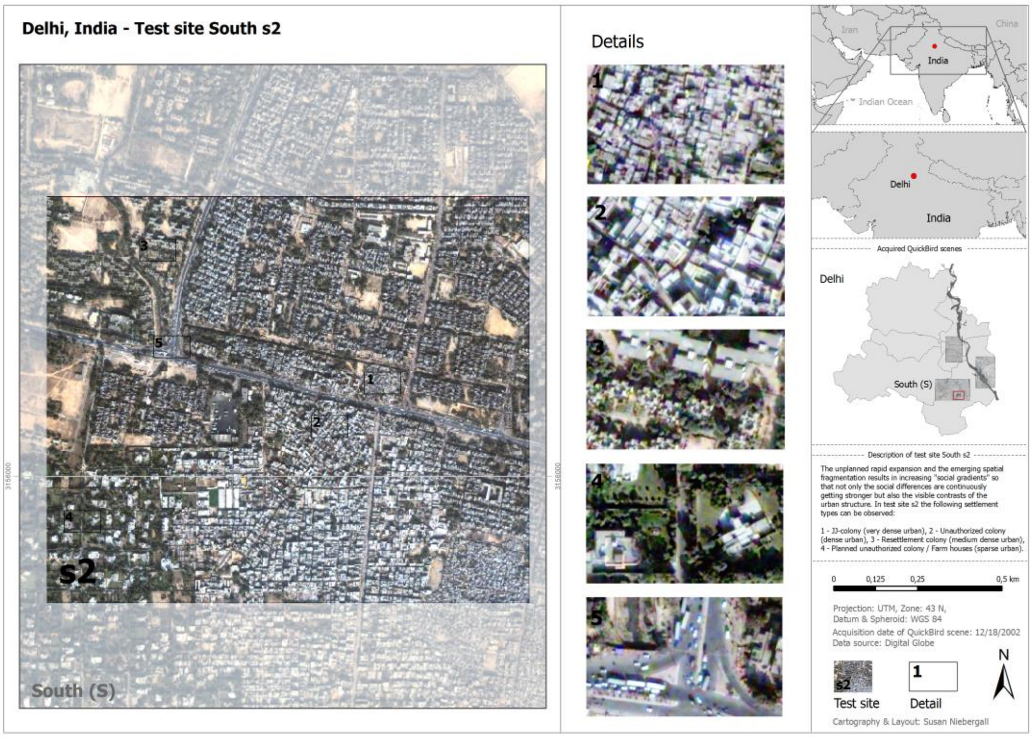
Further land cover types are: 4 - Vegetation, 5 - Not impervious.

Projection: UTM, Zone: 43 N,
Datum & Spheroid: WGS 84

Acquisition date of the QuickBird scene: 12/18/2002
Data source: Digital Globe

Cartography & Layout: Susan Niebergall

Map 4-3: Overview of test site South s3 and detailed view of the settlement types occurring within this area. Within the map moreover the training area is included as 4/3/2 composite (for an enlarged map cf. Appendix, A.4).



Description of test site South s2

The unplanned rapid expansion and the emerging spatial fragmentation results in increasing "social gradients" so that not only the social differences are continuously getting stronger but also the visible contrasts of the urban structure. In test site s2 the following settlement types can be observed:

1 - JJ-colony (very dense urban), 2 - Unauthorized colony (dense urban), 3 - Resettlement colony (medium dense urban), 4 - Planned unauthorized colony / Farm houses (sparse urban).

Projection: UTM, Zone: 43 N,
Datum & Spheroid: WGS 84

Acquisition date of QuickBird scene: 12/18/2002
Data source: Digital Globe

Cartography & Layout: Susan Niebergall

Map 4-4: Test site South s2 and corresponding details of the settlement types occurring within this area (for an enlarged map cf. Appendix, A.5).

Chapter 5

Data Used

This chapter provides a summary of all the data used in the present study. In the first section (chapter 5.1), the remote sensing data processed and analyzed is presented. Also the required pre-processing of the satellite images is given here. The second section

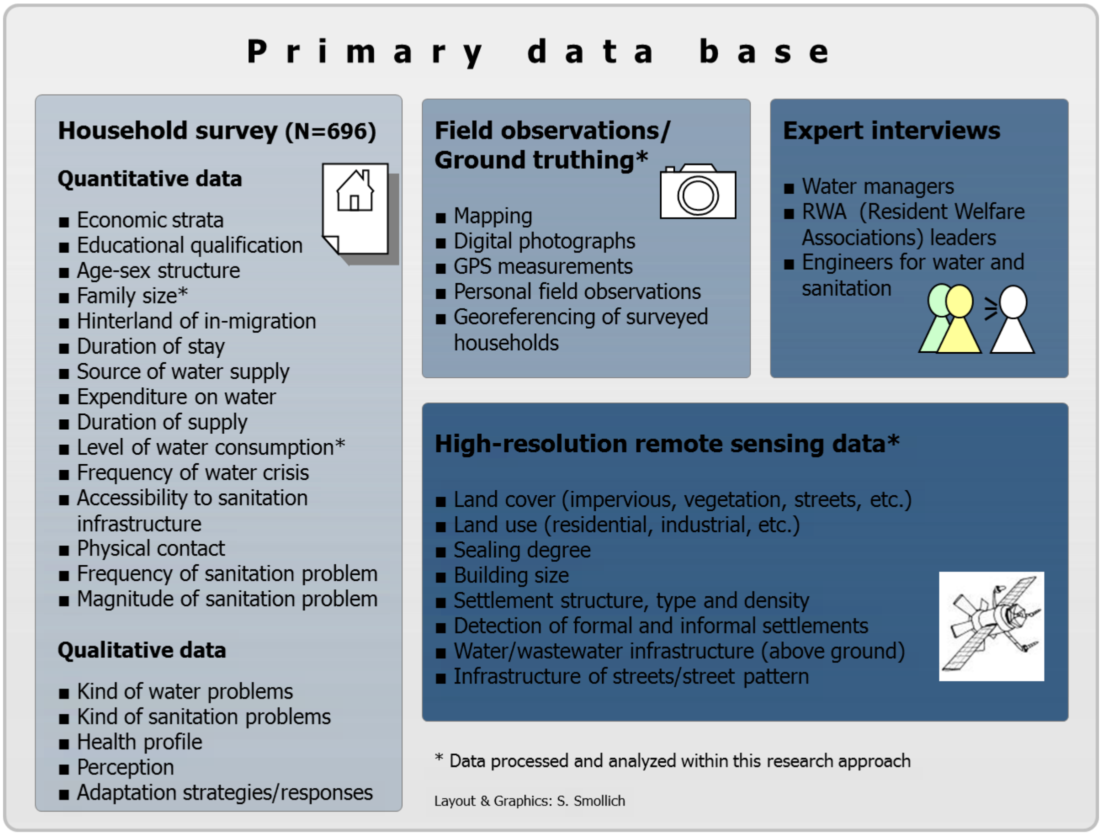


Figure 5-1: Overview of the primary data base using in the research initiative.

(chapter 5.2) introduces the primary data of the household survey collected during field campaigns in the Delhi study sites. Apart from the questionnaires, additional information was gathered through personal observation techniques, digital photograph documentation and GPS measurements. The data base generated with the aforementioned methods (is mainly used for validation purposes and) is described in chapter 5.3. An overview of the primary data base used in this research is shown in Figure 5-1.

5.1 Remote Sensing Data

The analysis of heterogeneous, high-fragmented and dynamic urban environments requires the application of very high-resolution (VHR) satellite data. The specification VHR is commonly used for spatial resolution with a ground sampling distance (GSD) of < 1 m (MOELLER 2005) (cf. Table 3-3). A number of panchromatic and multispectral sensors operating as VHR systems are available. For detailed information on current VHR sensors see chapter 3.2.1.

QuickBird data is used in the present study to examine the potential of satellite images to identify informal settlements and other settlement types by their visible spatial structures and dynamics. Since the successful launch of Digital Globe´s^{TM} QuickBird satellite in October 2001 and the availability of the data, QuickBird imagery has quickly become a popular choice for large-scale mapping using VHR satellites. QuickBird has a 97.2° sun-synchronous near polar orbit at 450 km altitude (URL 7). The QuickBird sensor is one of the first commercial satellites that provides sub-meter resolution imagery (KLEINSCHMIT ET AL. 2007). According to that, QuickBird collects multispectral and panchromatic imagery concurrently, at resolutions of 2.44 – 2.88 m and 0.61 – 0.72 m at nadir respectively (CHENG et al. 2003 & URL 7). A total of five bands are acquired, whereas the panchromatic band is ranging from 0.45 - 0.9 µm and the multispectral bands (blue, green, red and near Infrared) are ranging also from 0.45 - 0.9 µm (URL 7). Thus, by using data fusion techniques, the multispectral bands can be easily merged with the panchromatic (POHL & VAN GENDEREN 1998, ROSSI 2003). QuickBird panchromatic imagery is collected in 11-bit format (2048 gray levels). A big advantage of the 11-bit resolution is the possibility to differentiate further details for instance in urban shadowed areas. QuickBird has along-track and/or across-track stereo capability, which allows for a high revisit frequency of one to 3.5 days, depending on the latitude (TOUTIN & CHENG 2002, ROSSI 2003 & URL 7). The sensor's nominal swath is 16.5 km (at nadir) (CHENG ET AL. 2003 & URL 7). A summary in Table 5-1 briefly introduces the technical features of the QuickBird sensor. The combination of very high-resolution, high-revisit frequency and large area coverage is certainly it´s major advantage over the use of aerial photos or (usual) multispectral satellite data. For more detailed information on the QuickBird sensor characteristics and different products see TOUTIN & CHENG (2002) as well as URL 7.

Table 5-1: Technical features of the QuickBird sensor

Orbit information	Altitude	450 km
	Inclination	97.2° (sun-synchronous)
	Equator crossing time	10:30 AM
	Nominal swath width	16.5 km (at nadir)
	Revisit time	1-3.5 days
	Max. view angle	30°
Dynamic range		11 bits per pixel
Geometrical resolution	Panchromatic	0.61m (nadir) - 0.72m (25° off-nadir)
	Multispectral	2.44m (nadir) - 2.88m (25° off-nadir)
Spectral coverage	Panchromatic	450 – 900 nm
	Multi-spectral	
	Blue	450 – 520 nm
	Green	520 – 600 nm
	Red	630 – 690 nm
	NIR	760 – 900 nm
Spatial coverage	Area mode	16.5 x 16.5 km
	Strip mode	16.5 x 165 km (single pass)

Data source: URL 7

5.1.1 Acquired Image Data

To best capture the heterogeneous nature of Delhi three different QuickBird images are used to cover different parts of the urban agglomeration (cf. Map 4.1 in chapter 4.2). All three scenes are so-called Standard Imagery Bundles. Users of QuickBird´s Standard Imagery products usually possess sufficient knowledge to manipulate and exploit the imagery for a wide variety of applications. Thus, Standard Imagery products are designed for users acquainted with remote sensing applications and image processing tools that require data of modest absolute geometric accuracy and/or small area coverage. Each Standard Imagery product is radiometrically calibrated, sensor corrected, geometrically corrected, and mapped to a cartographic projection. It has an absolute geometric accuracy in the desired map projection of up to 14 meters (RMSE), excluding any topographic displacement (TOUTIN & CHENG 2002, URL 7). For more information on the radiometric and geometric corrections applied by Digital Globe see URL 7.

The data for the Delhi study area was acquired on April 20th 2002 (Central '02), on September 19th 2002 (East) and December 12th 2002 (South), respectively. The central image of Delhi covers an area of almost 42 km^2, the eastern image about 57 km^2, while the image situated in the South covers an area of about 69 km^2 (cf. Map 4-1). For all acquisitions a nadir-mode was requested granting minimal viewing angles. Table 5-2 gives a detailed overview of the QuickBird scenes processed and analyzed in the framework of this thesis.

Table 5-2: Meta data of the QuickBird scenes processed and analyzed

Internal name	Collecting date	Sensor ID	Product type	NW corner		SE corner		Area	Off-nadir	Cloud cover
				Latitude	Longitude	Latitude	Longitude	[km²]		[%]
Central ´02 (C02)	04/20/2002	QB02	OR Standard*	28.6759204	77.19226817	28.60521292	77.24499576	41.92	13.1°	0
East (E)	09/19/2002	QB02	OR Standard	28.61834169	77.28517664	28.53330788	77.34591498	57.48	13.0°	0
South (S)	12/18/2002	QB02	OR Standard	28.55962427	77.15809839	28.50041436	77.26492684	69.20	13.3°	0
Central ´06 (C06)	05/29/2006	QB02	OR Standard	28.67125439	77.19208271	28.62706533	77.2449132	26.12	11.0°	0

* Standard Imagery products are radiometrically corrected, sensor corrected, geometrically corrected, and mapped to a cartographic projection.
Map projection / map zone, hemisphere: UTM, WGS 84 / 43 N
Data source: Digital Globe

The test areas were selected based on prior local knowledge of the city. Within the test areas, a total of seven single test sites have been chosen. The test sites show a high socio-economic gradient and large visible contrasts within short distances. Moreover, a training area inside test site s3 was selected (cf. Map 4-3 and A.4) The chosen training area shows several forms of settlement structures beneath middle class residential districts and informal settlements. More information regarding the selection of useful test sites within Delhi and their features can be found in chapter 4.2 and chapter 5.3. At a first stage the data analysis steps were tested at this area. The developed methodology was then transferred to the whole test site and other areas correspondingly.

5.1.2 Pre-processing of the Satellite Data

Prior to the classification and analysis of the satellite data some pre-processing was necessary. In order to benefit from panchromatic high spatial resolution (0.6 m) simultaneously with multispectral information, a resolution merge was performed before analyzing the images. Since the panchromatic and multispectral image bands fit well due to a parallaxis correction undertaken by the data provider they can easily be fused to integrate the high spatial information content of the panchromatic band into the multispectral bands. In this study, the primary objective of the fusion is defined to preserve the spectral information, while enhancing the spatial variability. Therefore, additive pan sharpening algorithms, such as the Brovey transformation were not considered here (KLEINSCHMIT ET AL. 2007 & VRABEL 1996). Instead of that, some tests with other standard algorithms provided by commercial image analysis software packages were carried out, e.g. the Multiplicative method and the Principal Component Analysis (PCA) combined with Nearest Neighbor, Bilinear Interpolation as well as Cubic Convolution as resampling technique. Moreover, a Wavelet PCA and a Wavelet Intensity-Hue-Saturation (IHS) were performed to test the quality of the information fusion. Finally, the PCA pan sharpening method with cubic convolution yielded the best results with respect to the radiometric and geometric characteristics of the original images and proved therefore to be the most successful in pan sharpening the present QuickBird images (cf. Figure 5-2) (EHLERS 2005, HOFMANN 2001a, POHL

& VAN GENDEREN 1998). Thus, all of the analyses carried out in this work and their results are based on the merged QuickBird data.

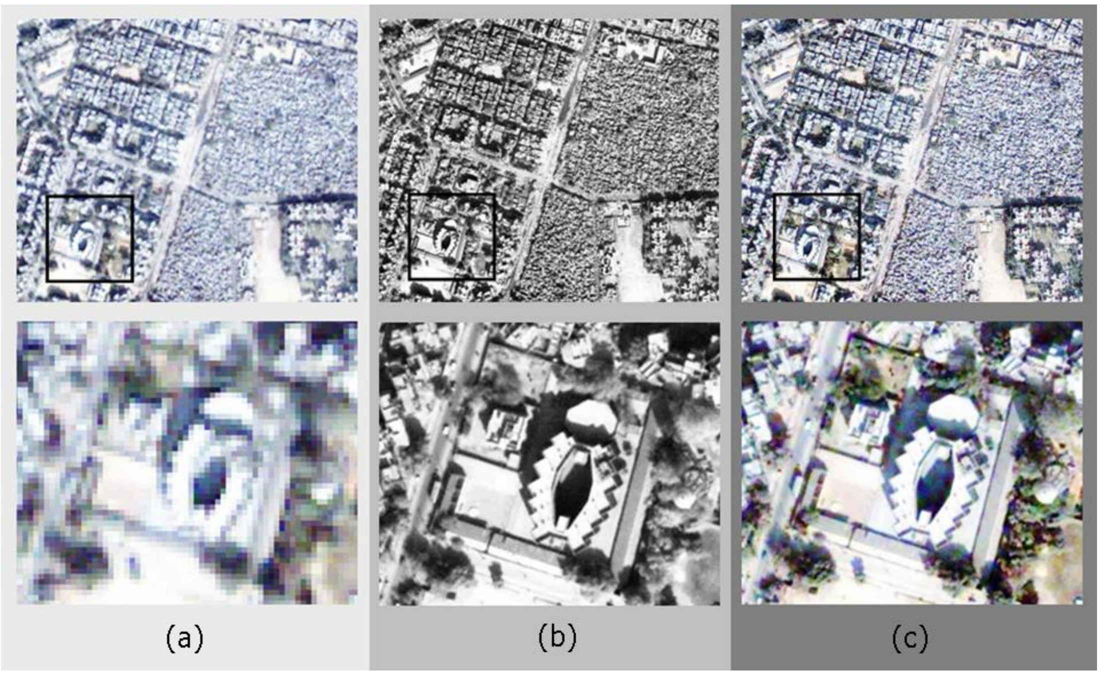


Figure 5-2: Results of the Principal Component Analysis (PCA) pan sharpening of the QuickBird data, subset of the scene South (S): (a) 2.4 m multispectral (3/2/1), (b) 0.6 m panchromatic, and (c) 0.6 m fused image (3/2/1).

5.2 Household Survey

> "One of the chief practical obstacles to the development of social inquiry is the existing division of social phenomena into a number of compartmentalized and supposedly independent non-integrating fields."
>
> (John Dewey 1938 in JOHN GERRING 2001)

In association with the research initiative an intense field campaign was conducted in 2005 and 2006 to sample in-situ information. Primary household data were collected through personal observation and household surveys within the selected test sites (cf. Map 4-2). In order to get an additional perspective of the living conditions and supply situation of the different settlement types of Delhi, meetings with responsible local and state officials were arranged and several expert interviews were conducted within this research initiative (cf. Figure 5-1). These respondents included key informants and leaders of *Resident Welfare Association*s *(RWA)*, persons in charge of the municipal water board *(DJB - Delhi Jal Board)* as well as engineers for water and sanitation of the distinct localities. Since the remote sensing approach is following a quantitative approach, the results of these interviews were hardly taken into consideration within this study. These are of higher importance for the two other research approaches which include the expert interviews in their analysis (cf. SELBACH 2009 & SINGH 2008). Details of the questionnaire design, the empirical phase and the evaluation of the household survey as well as their critical appraisal are described in the following subchapters.

5.2.1 Questionnaire Design

To get a broad overview of the heterogeneous living conditions and the very complex supply situation of Delhi's inhabitants, a standardized and structured questionnaire was developed. This questionnaire was designed to extract quantitative and qualitative information about (a) the socio-economic background and (b) the water availability and consumption pattern of the people (which is deemed to be necessary in order to anticipate the quantities of water demand as well as wastewater generated, as well as its disposal mechanism and routes of exposure). A part of the questionnaire was also devoted to a basic health survey (c). Moreover, it included sections to cover people's perception and response to existing water and sewage situation and preferred solutions (d) (NIEBERGALL ET AL. 2009).

The questionnaire contains primarily closed-ended questions. In a closed-ended question the response categories are provided, and the respondent just chooses between the clearly phrased answers. The main advantages of this question type are: (1) quick to answer, (2) easy to code, (3) no difference between articulate and inarticulate respondents, and (4) easy to replicate study. However, closed-ended questions can draw misleading conclusions because of limited range of options or can force respondents into simple responses (URL 10 & 11). In connection with this, also open-ended questions were included in the questionnaire (SELBACH 2009). In an open-ended question no standard answers to choose from are provided. The main advantages of open-ended questions are: e.g., (1) greater freedom of expression, (2) no bias due to limited response ranges, and (3) respondent can qualify and clarify their answers (URL 10 & 11). Since the coding is very time consuming and the interviewer may misinterpret (and therefore misclassify) a response, this type of questions can affect the household survey adversely.

To cope with all three research approaches quantitative and qualitative, open-ended as well as closed-ended questions were included in the interview. Comparable to the selection of the test sites earlier, the following basic assumptions were here also taken into account: on the one hand, the high morphological, structural fragmentation of the spatial units, relevant out of the remote sensing perspective, and on the other hand the differentiation of the settlement types, which are important from a social and urban geographical view (cf. chapter 4.2). Furthermore, the questionnaire included narrative parts, which answers were recorded for later references. In this study, however, only closed-ended, quantitative questions are taken into account in the evaluation.

Based on a common questionnaire design process (cf. Figure 5-3) the questionnaire was drafted jointly by all three PhD candidates during the preliminary phase, with the prerequisite to obtain an identical interview situation for all respondents. With this standardization, different possibilities of interpretation of identical questions, due to different phrasing, should be avoided. The respective interesting questions for all three different research approaches were implicated in the survey, resulting in the compilation of an "integrative questionnaire".

The questionnaire, which is attached in original in the Appendix (cf. A.15), comprises questions of different categories including "knowledge questions", "action or behavior questions" as well as "opinion or attitude questions" (MEIER KRUKER & RAUH 2005, SELBACH 2009). Within this study, first and foremost "knowledge questions" are relevant for the further analysis since they usually refer to the personal and demographic characteristics. By means of these questions, information about the personal background (e.g., age, education and caste, size of household, income or settlement type) and the supply situation (e.g., water supply) was collected. With this information, statements concerning the socio-economic situation of the questioned households could be derived. In turn, this information is important for the investigation of the coherence between settlement structure and derivation of living conditions. More details about the questionnaire design can be found in SELBACH (2009) and SINGH (2008), respectively.

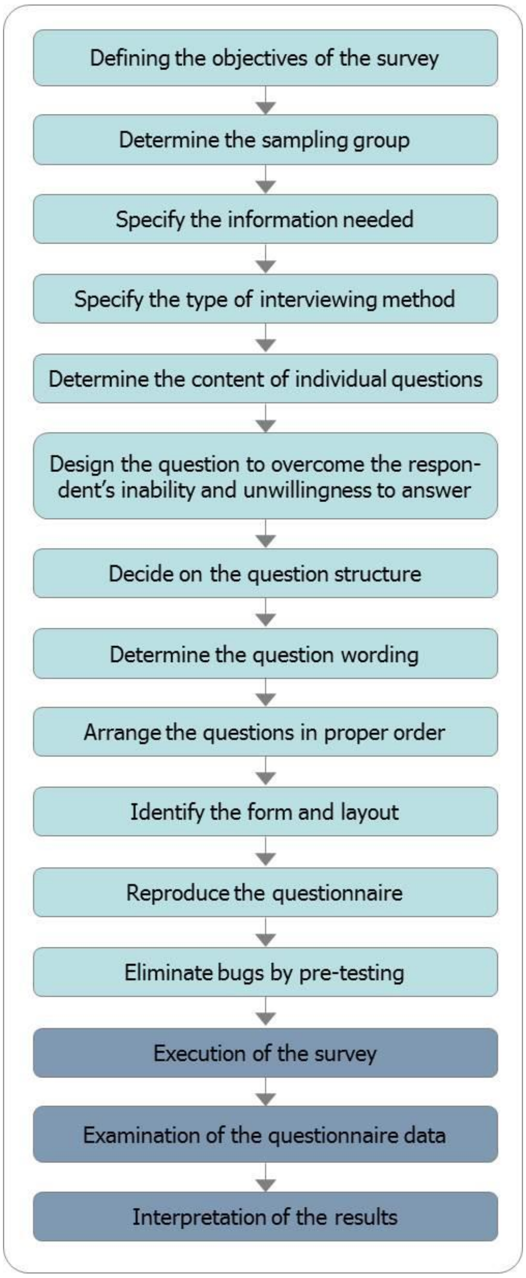


Figure 5-3: Questionnaire design process *(Source: BRADBURN 2004 & STAHEL 2002).*

5.2.2 Empirical Phase of the Household Survey

During the first field campaign between September and October 2005 the preselection of the study areas in which the survey should be carried out was verified. At the same time, the questionnaire was tested on its applicability. Prior to the actual household survey, the questionnaire was pre-tested in order to check whether it yielded comprehensible and relevant responses, and adjustments were made accordingly. After revision, the first acquisition phase of primary data in three of the seven test sites was carried out from October to November 2005. This survey and the following were conducted by the PhD candidates Veronika Selbach and Reena Singh, with the support of students of the *Delhi University* who were carefully trained to administer the designed household questionnaire (KRAAS ET AL. 2007d). Each household interview took 45 minutes on average.

Stratified purposive-random sampling techniques[9] (STAHEL 2002) were applied to choose the respondent household from various kinds of settlements, including JJ-clusters (equivalent to informal settlements), resettlement areas, gated communities, government quarters and different types of unauthorized colonies as well as urban villages (cf. chapter 4.1, Table 4-3). Hence, the affiliation to a certain social class (from upper to lower class) and an adequate representation of all socio-economic hierarchies were kept in view comparably. Moreover, the location of the households within the different morphological structures displayed in the satellite data, combined with the structure densities of the settlements, was taken into consideration regarding the choice of the households.

A total survey of all households in the respective areas under investigation would be statistically absolutely correct. This is, however, generally unfeasible and also in this special case impossible for reasons of economy, time and practicability. Primarily due to the difficult conditions on the spot, e.g., skepticism and rejection by the respondents, cultural circumstances or sometimes the impreciseness of the interviewer, a real random sampling was not feasible in the study areas of Delhi. In this regard, the tremendous amount of dwellers within the test sites has to be mentioned and, thus needs to be included in the group of reasons. Also the execution of a cluster sample[10] would statistically be correct (STAHEL 2002), but was not realizable for the reasons mentioned. Under these constraints the above described statistical approach appeared to be the most suitable to generate a

---

[9] "Stratified … random sampling is a variation of simple random sampling in which the population is partitioned into relatively homogeneous groups called strata and a simple random sample is selected from each stratum. The results from the strata are then aggregated to make inferences about the population. A side benefit of this method is that inferences about the subpopulation represented by each stratum can also be made" (URL 12).

[10] A cluster sampling is a sampling technique where the entire population is divided into groups or clusters, and a random sample of these clusters is selected. All observations in the selected clusters are included in the sample (GERRING 2001 & STAHEL 2002).

valuable data basis and was consequently chosen for this study (cf. SELBACH 2009 & SINGH 2008).

The completion of the data collection in the remaining four test sites using the standardized questionnaire was carried out from February to April 2006. Key informants of the households were interviewed, including both female and male household members. For conclusions regarding the understanding of gender based differences in the perception of the respondents a relationship of 50:50 was striven (cf. Figure 5-5). The questionnaire was prepared both in English and in Hindi, to make the questions as understandable as possible for the respondents.

After the survey, the questionnaire data collected was analyzed in different ways according to its statistical features. The evaluation is described in more detail in the following subchapter. Further results, e.g., average family size or average water amount per family in different settlements, are presented in chapter 6.2.

5.2.3 Evaluation of the Survey Data

In total 696 households were interviewed, covering a population of 4,358 persons residing in different types of settlement (cf. Figure 5-4). According to WEEKS (2001) demographic research that employs spatial analysis obviously requires data that are georeferenced. If data are not assigned to a certain location, then spatial analysis is not feasible. Therefore, all questionnaires were georeferenced and embedded in a GIS environment (cf. Map 5-1 and Map 5-2). Within test site South s3 96 interviews were carried out, 148 households were surveyed in the transfer site South s2 (cf. Figure 5-5).

In a first step, the collected data was transferred in a data matrix in which each household represents a subject of investigation. The open-ended questions and other quoted remarks were transferred in their original text form. The variables collected continuously were as well taken in their original expression (e.g., age, number of household members). In contrast to that, the discrete variables (e.g., income, level of education) were transferred using a coding key (cf. Appendix III in SELBACH 2009).

In a second step, these discrete variables were classified, respectively partly new variables, which could be generated from the responses of the households, were generated. Within this process a suitable class number, class width and class limit could not always be found and fixed for the data. Aiming at receiving a maximum of information with a minimum of classes, a decision which is subjective and adapted to the data was taken for the generation of suitable class numbers (MEIER KRUKER & RAUH 2005, SELBACH 2009).

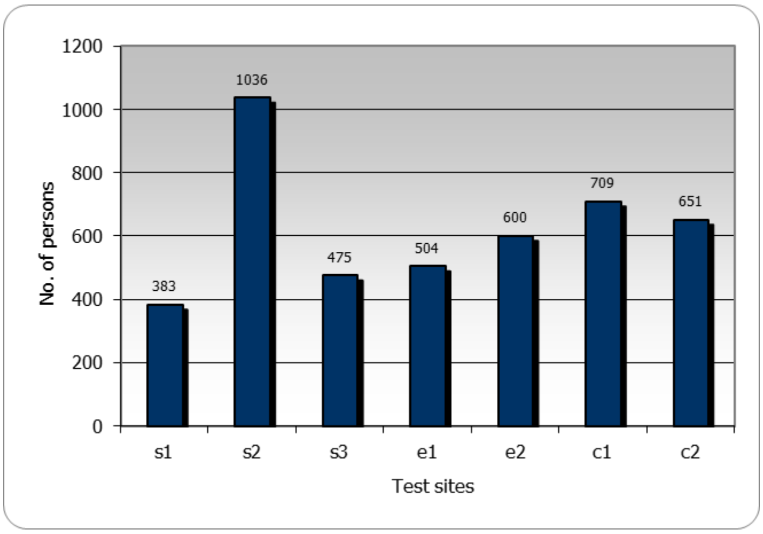
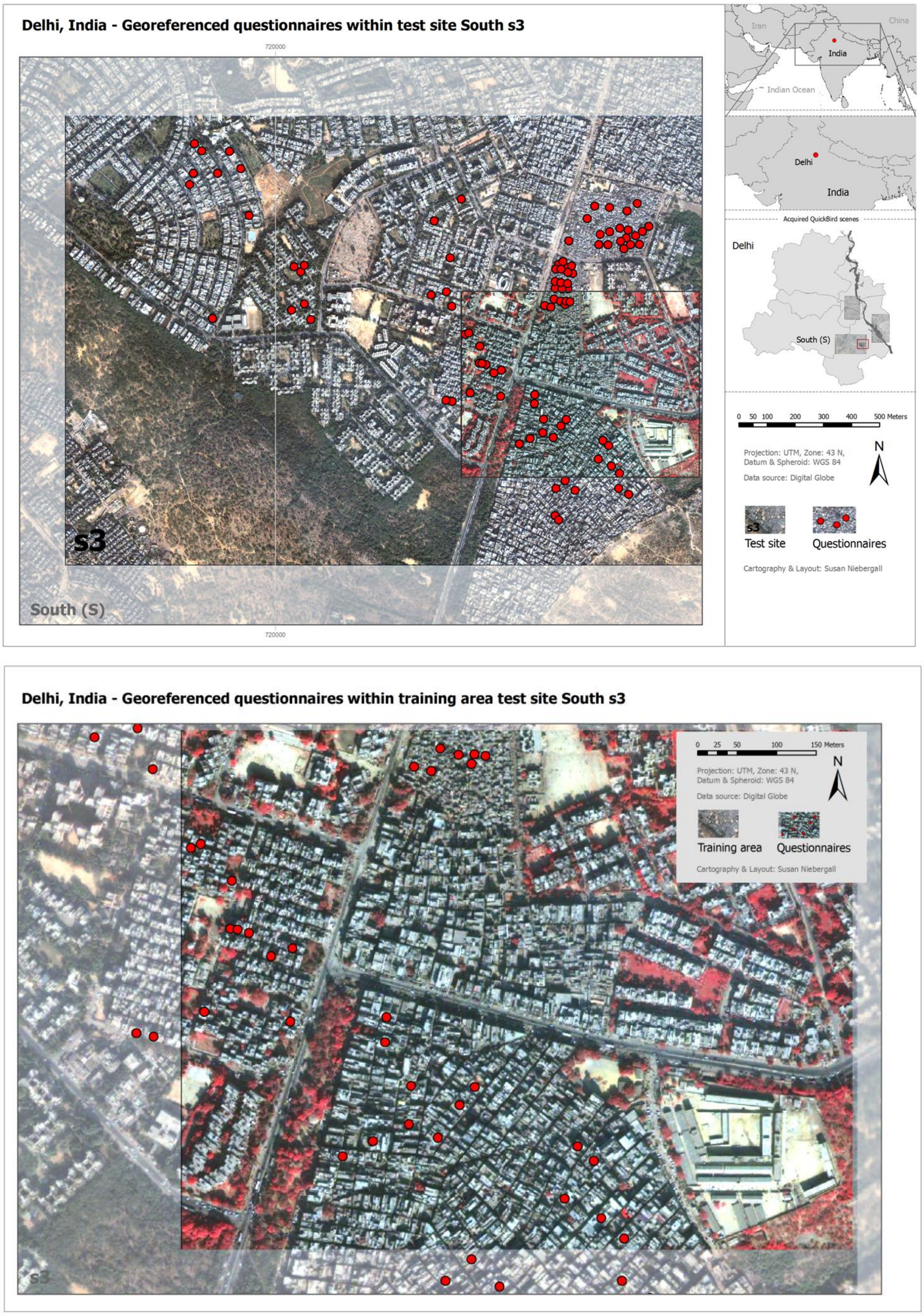


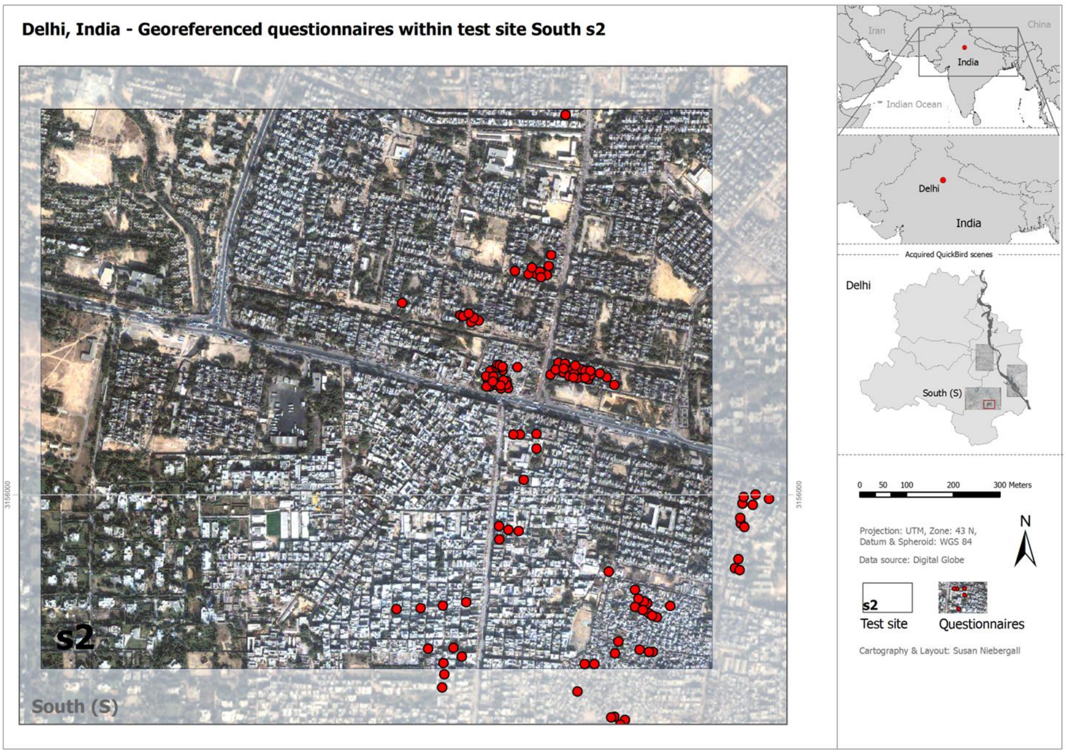
Figure 5-4: Total population of the surveyed households within chosen test sites in Delhi (N=696) *(Data source: household survey 2005-2006)*.

The categorization of the data was made by an intuitive procedure considering "meaning thresholds". The reasons for this decision are described in detail by SELBACH (2009). The "meaning thresholds" can on the one hand be justified by external official guidelines (e.g., incomes, required water quantity per person per day). On the other hand, they can be derived from findings, which are logically comprehensible and which were gained during the data survey or during the evaluation process (e.g., number of people per household, age). This means, that the evaluation of the survey data is partly characterized by a subjective point of view. The classes are accordingly not always equally represented, which must be taken into account while interpreting the results.

In this study, the following analysis was carried out by means of common practice statistical methods (cf. also chapter 6.2). In order to improve the assessment of the individual analysis results, which are described in the following chapters, it is important to get firstly a general overview of the data and of the people interviewed accordingly. Particularly, the family or household level is at the base of any socio-economic process a region is undergoing. Outlining the characteristics of the population covered is therefore a prerequisite to understand the situation, processes and developments occurring there (KRAAS ET AL. 2007d).



Map 5-1: Georeferenced questionnaires within test site South s3 (top) and the chosen training area (bottom) (for enlarged maps cf. Appendix, A.7.1 and 7.2).



Map 5-2: Georeferenced questionnaires within the transfer test site South s2 (for an enlarged map cf. Appendix, A.7.3).

In this regard, at the beginning of the evaluation the demographic, economic and educational data of the surveyed households were processed to give general background information about the surveyed population. The information which was extracted from the surveyed questionnaire and then processed is graphically represented below in Figure 5-5 and Figure 5-6.

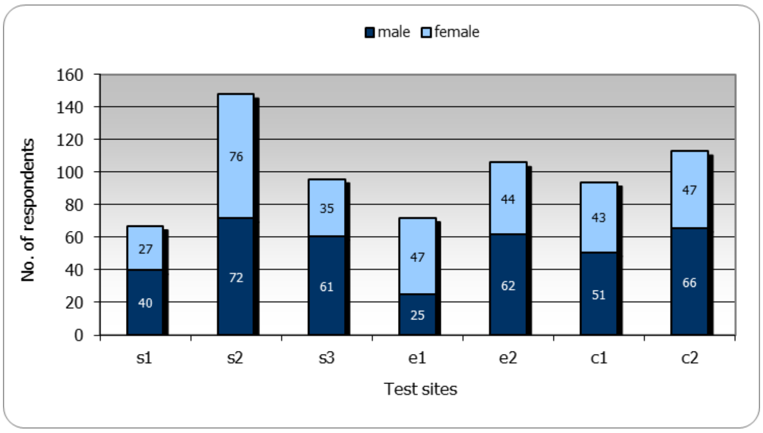


Figure 5-5: Total number of household male and female respondents interviewed within chosen test sites in Delhi *(Data source: household survey 2005-2006).*

As can be seen in Figure 5-6, there are clear demographic differences regarding the distribution of the surveyed households by family size between the individual selected test sites. These strong contrasts within the test sites become as well apparent during the evaluation of the questionnaires. Thus, the proportion of the families with five to eight members within test site South s2 is considerably larger than that one of the remaining categories. The proportion of families with nine to 12 or more than 12 persons respectively is also comparatively large in test site South s2. These conditions indicate a large proportion of residents of the lower class. In contrast to this, the number of households interviewed with two to four members in test site South s3 is almost equal as the number of households with five to eight members.

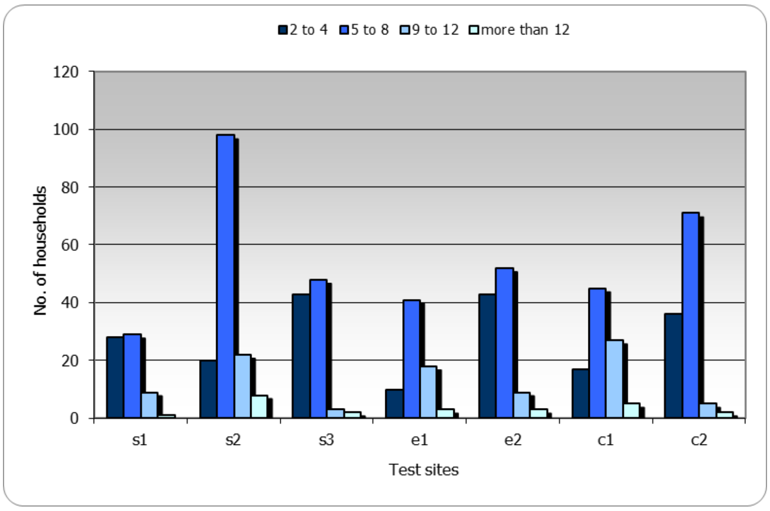


Figure 5-6: Distribution of the surveyed households by family size (N=696) *(Data source: household survey 2005-2006).*

The categories with more than eight members per family are occupied very weakly. This speaks for a large number of detached houses, what, in turn, is a sign of a large proportion of middle and upper class inhabitants. Interpreting this data it is important to consider that the conduction of interviews with members of the upper class during the survey was very difficult (cf. chapter 5.2.4). An interview in this social class was often declined, while the members of the lower class have, due to their bad living conditions, usually agreed to an interview very willingly. Hence, the proportion of families with two to four persons of the total population is slightly underrepresented in the respective test site. However, a trend for the social structure of the population can certainly be derived.

Additional figures for the estimation of socio-economic structure and supply of basic infrastructure of surveyed households and different settlement types, respectively (e.g., distribution of households by monthly income, educational qualifications of the respondents, percentage of sample households connected to sewer system, estimated wastewater generation in different settlement types etc.) as well as the corresponding descriptions can be found at KRAAS ET AL. (2007d), SINGH & KRAFFT (2007) and SINGH (2008).

Further analysis of the questionnaire data were conducted with direct response to this study (i.e. the remote sensing part of the research initiative) and the implemented integrative analysis (cf. chapter 6.2 and 8). To describe this briefly, the integrative analysis is used to determine different socio-economic attributes (e.g., population amount or population density) and to evaluate the water demand within a certain settlement area. For this purpose various settlement characteristics like house size or number of houses are estimated from the satellite data and are used to derive spatial information about the population distribution. In addition to that, the integrative approach makes use of the georeferenced questionnaires in order to characterize a given settlement type in terms of specific population and water related variables. Hence, for instance the family size or the mean water consumption per capita in different residential areas and settlement types respectively are calculated and considered in this analysis (cf. Figure 5-7 and Figure 5-8).

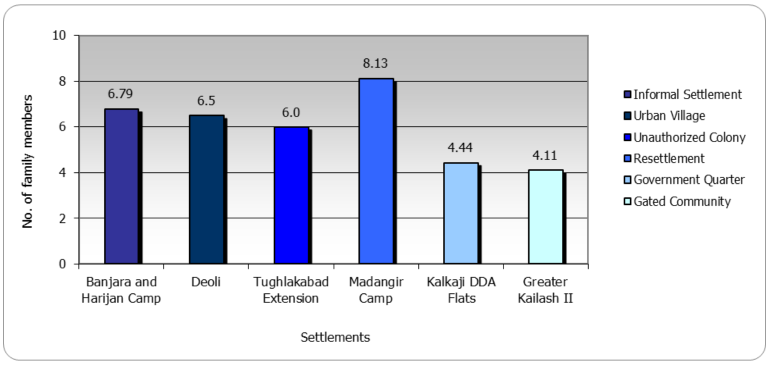


Figure 5-7: Family size in different settlement types within test site South s2 and South s3 in Delhi *(Data source: household survey 2005-2006)*.

Primarily informal settlements are subject to high dynamics, population density as well as marginalization. In regard to the living conditions of the dwellers and the corresponding need for action in these colonies, the evaluation of the interview data of informal settlements is of special importance (cf. Figure 5-9 and Figure 5-10).

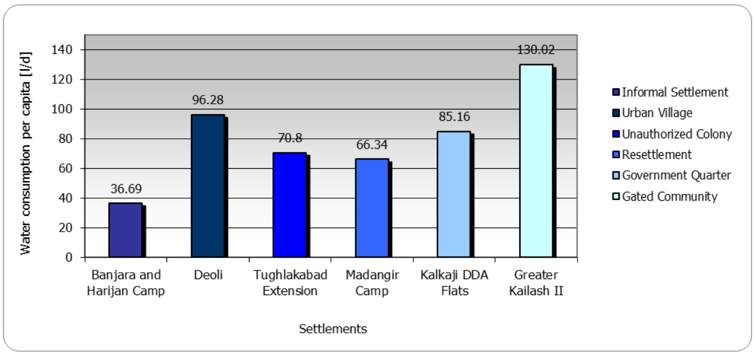


Figure 5-8: Water consumption per capita per day in different settlement types within the selected test sites South s2 and s3 in Delhi *(Data source: household survey 2005-2006)*.

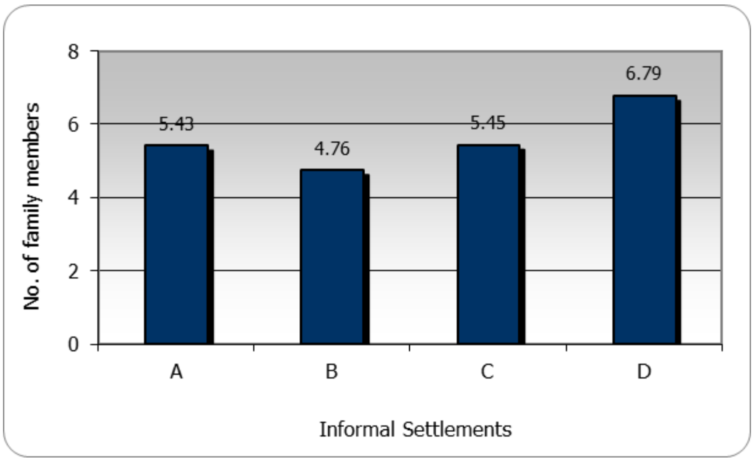


Figure 5-9: Family size in different informal settlements for selected test sites in Delhi (s2, s3): A — Bhomiheen Camp (training area), B — Bhomiheen Camp (total), C — Nehru and Navjeewan Camp, D — Banjara and Harijan Camp. Settlement A – C are situated within test site South s3, settlement D is situated within test site South s2 *(Data source: household survey 2005-2006)*.

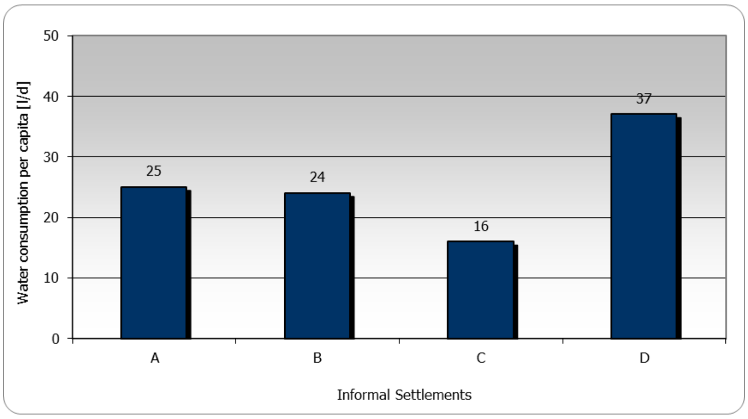


Figure 5-10: Water consumption per capita per day in different informal settlements for selected test sites in Delhi (s2, s3): A — Bhomiheen Camp (training area), B — Bhomiheen Camp (total), C — Nehru and Navjeewan Camp, D — Banjara and Harijan Camp. Settlement A – C are situated within test site South s3, settlement D is situated within the transfer test site South s2 *(Data source: household survey 2005-2006)*.

5.2.4 Appraisal of the Survey Data

In the following chapter the execution of the survey is subjected to a short review and is discussed critically. Some facts are pointed out, which are necessary to be included in the examination and assessment of the following integrative analyses. Table 5-3 shows a general overview of the potential causes for the bias of responses during an interview.

The questionnaire proved to be very comprehensive, so that partly a shortening of the interview or a lower depth of detail in the replies had to be accepted due to the restricted time frame of the interview partners. In rare cases the interviewed persons even terminated the interview. The reason for this was not only the limited time factor but sometimes also a fundamental mistrust of the interviewees. For this study, however, this circumstance is negligible since here solely quantitative questions, which could be answered briefly, were included in the evaluation. If the respondents did not answer ingenuous, the interview was also stopped in rare cases on the part of the interviewer. Sometimes the assumption arose during the interview or at the evaluation of the questionnaires that the given answers do not correspond to reality. This was partly caused, depending on the situation, by the presence of third persons (extenuation or dramatization of the living conditions). For this reason single questionnaires were sorted out from the sampling afterwards.

Table 5-3: Bias of answers running a survey

Characteristics of the respondents	
Social desirability of the responses	Return of socially desirable responses
Non-Opinion	Return of a "don't know" or "cannot remember" - response, e.g. in case of unpleasant topics
Non-Response (unwillingness)	Refusial to give a response to a certain question or to the complete questionnaire
Non-Attitudes	Giving a response, although no opinion on the asked topic or object is developed
Presence of a third person	Reactions to the presence of a third person during the interview
Effects of the interviewer	
Characteristics of the interviewer	Reactions to characteristics and behaviours of the interviewer (e.g. suggestive influence, pushing)
Fake of interviews	
Question features	
Halo- Effect	The positioning of questions in different parts of the questionnaire may lead to different responses due to the "emission" of previous questions

Source: SELBACH 2009 after MEYER KRUKER & RAUH 2005, modified; supplemented by STAHEL 2002

Again and again, ignorance or a poor educational background of the respondents resulted in all question areas in answers which in principle must be doubted. Consequently a certain error ratio should be also taken into account for the quantitative information (e.g., water consumption) which is used in this study. During the evaluation of the interview data, in particular the responses of the residents of lower class settlements showed outliers in the samples (cf. chapter 8). Moreover, the intended homogeneity of the sampling within the test sites proved to be unrealizable. While the population of the comparatively poor settlements of the lower class was generally available for an interview willingly, it was almost impossible to interview residents of the Gated Communities or other quarters of the higher middle class and upper class to collect a numerically equivalent amount of data in the respective settlement types. Therefore, the results related to the settlement types, particularly those of the upper middle and upper class are to be interpreted as a tendency and not as universally valid, quantitative representative probabilities.

Furthermore, the simplified assumption that every household represents a sampling unit finally turned out to be problematic during the evaluation of the interview data. That means, a house cannot always be equated with a household. Although, within the settlements of the lower class as well as the medium to higher upper class the assumption, that one family occupies one house, is applicable. Within the quarters of the middle class and lower upper class, however, in the majority of cases several families occupy one building. These are multiple-family dwellings or complete blocks of apartment buildings where normally each flat is occupied by one family. Statistics to the number of families per building were, however, not collected correspondingly. General assumptions must therefore be carried out during the evaluation of the data affected, which is in settlements with several accommodation units per building (e.g., DDA flats). For further studies this lack of information shows a potential for improvement.

Nevertheless, here, in the overall context the chosen approach has figured out to be successful. Only by using such an extensive sample a comprehensive overview of the living conditions as well as the complex problem of water supply and wastewater disposal could be generated in the respective settlement types of Delhi. From the knowledge-, action- and opinion-questions valuable results could be generated for all three research approaches. It is primarily the quantitative information which allows statements concerning the assessment of the living conditions and therefore builds a good basis for the consequent integrated analysis within this study.

5.3 Ancillary Field Data: Observations, Mapping and Ground Truthing

An intense field campaign was conducted in October 2005 to sample in-situ information. Apart from the questionnaire and guided interviews, thus, additional information was gathered through personal observation techniques, mapping and ground truthing (cf. Figure 5-1).

The field campaign in Delhi aimed at the identification of remarkable objects detected in the QuickBird data (verification or detection itself), the mapping and observation of different settlement types and structures, water related structures, as well as distinctive features or interesting points. Moreover, to link them with specific structures or features in the satellite images, digital photographs were taken in parallel to the ground mapping. As a whole the collected ground mapping and field data represent a good data base for the substantiation and validation of the results of this thesis.

During the household survey, the locations of the surveyed households were recorded using GPS measurements. Subsequent to the campaign, the respective coordinates were transferred into a GIS environment and corresponding maps were produced (cf. Map 5-1 and Map 5-2). Furthermore, using GPS measurements, the coordinates of remarkable objects, such as water towers or overhead water tanks, were collected and registered.

Following the field work, a basic evaluation of the field data and a visual interpretation of the QuickBird images were carried out. As shown in Figure 5-11, photographs of different settlement types were taken during the field campaign and afterwards compared with different settlement structures visible in the satellite data.

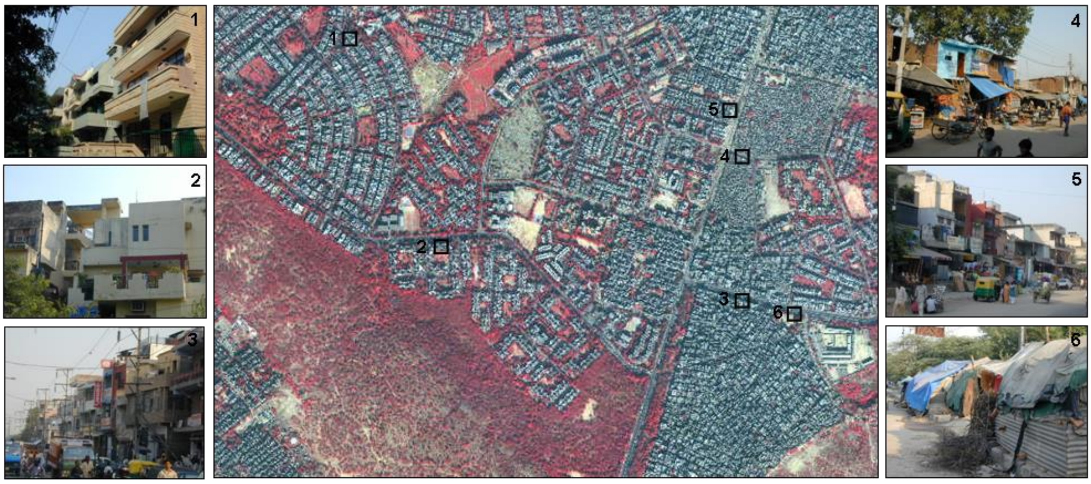


Figure 5-11: Test site South s3 (QuickBird scene South 12/18/2002) characterized by different settlement structures and corresponding photographs of different settlement types, taken during the field campaign in October 2005 in Delhi, India: 1 – Gated Community *Greater Kailash II* (authorized, planned, private colony), 2 – Government Quarter *Narmada* apartment houses (authorized, planned), 3 – Unauthorized Colony *Tughlakabad Extension* (unplanned), 4 – Jhuggi Jhompri cluster *Bhomiheen Camp* (unauthorized, informal), 5 – Resettlement Colony *Harijan Colony* (authorized, planned), 6 – Illegal quonset huts on the pavement close to *Tughlakabad Extension (Data source: Digital Globe, draft and photographs: Susan Smollich).*

In addition to that, based on the results of the ground mapping and local knowledge, in combination with a visible interpretation of the QuickBird images, density maps of the test sites were generated (cf. Figure 5-12 and Figure 5-13). These maps allow for a first general overview of the categories and features of settlement densities and their distribution in Delhi. In turn, these density maps can again be compared with the settlement types, which have developed in Delhi (cf. Table 4-3), with a special focus on their spatial characteristics as well as their living conditions. Moreover, the density maps are used for qualitative validation purposes of the classification results (cf. chapter 7).

Within this study, it could be proven that, at least as far as Delhi is concerned, the settlement density mostly correlates with the settlement type. Thus, the settlement density was included as a key parameter for the identification of Delhi's informal settlements (JJ clusters) in special and other settlement types in general (cf. chapter 6.1.2). On the basis of the obtained findings, combined with the satellite data for all chosen test sites in Delhi, altogether four density classes were defined: (1) very dense urban, (2) dense urban, (3) medium dense urban as well as (4) sparse urban areas. All other areas, which are not covered with buildings at all (e.g., areas covered with vegetation, not impervious areas) or which are not covered with residential buildings (e.g., industrial areas) are assigned to the class (5) not inhabited area. The defined density classes are characterized by the following physical parameters: (i) fraction of the impervious area (coverage of built-up area), (ii) fraction of vegetation surface and (iii) building size, and as a consequence, (iv) the amount of buildings per total settlement area (building density).

Figure 5-12: Density map of test site South s3 in the southern part of Delhi based on QuickBird scene South (12/18/2002) *(Data source: Digital Globe, draft: Susan Smollich).*

These parameters represent features that can be observed and received with the naked eye, on examination of the satellite images as well as by the on-site observation. Our ability to see the observed in a bigger context enables us to draw according logic consequences. This is known as an "intuitive process". This means, in this special case, that it is possible to define different density classes and to record them in a map.

Object-oriented analysis methods of satellite data also make use of these object features and the possibility to combine these characteristics. With the difference, that the fragmentation of the area and the classification of the respective objects are not carried out manually or completely visually but (semi-) automatically by means of a certain segmentation algorithm and a developed classification scheme and in an as objective way as possible.

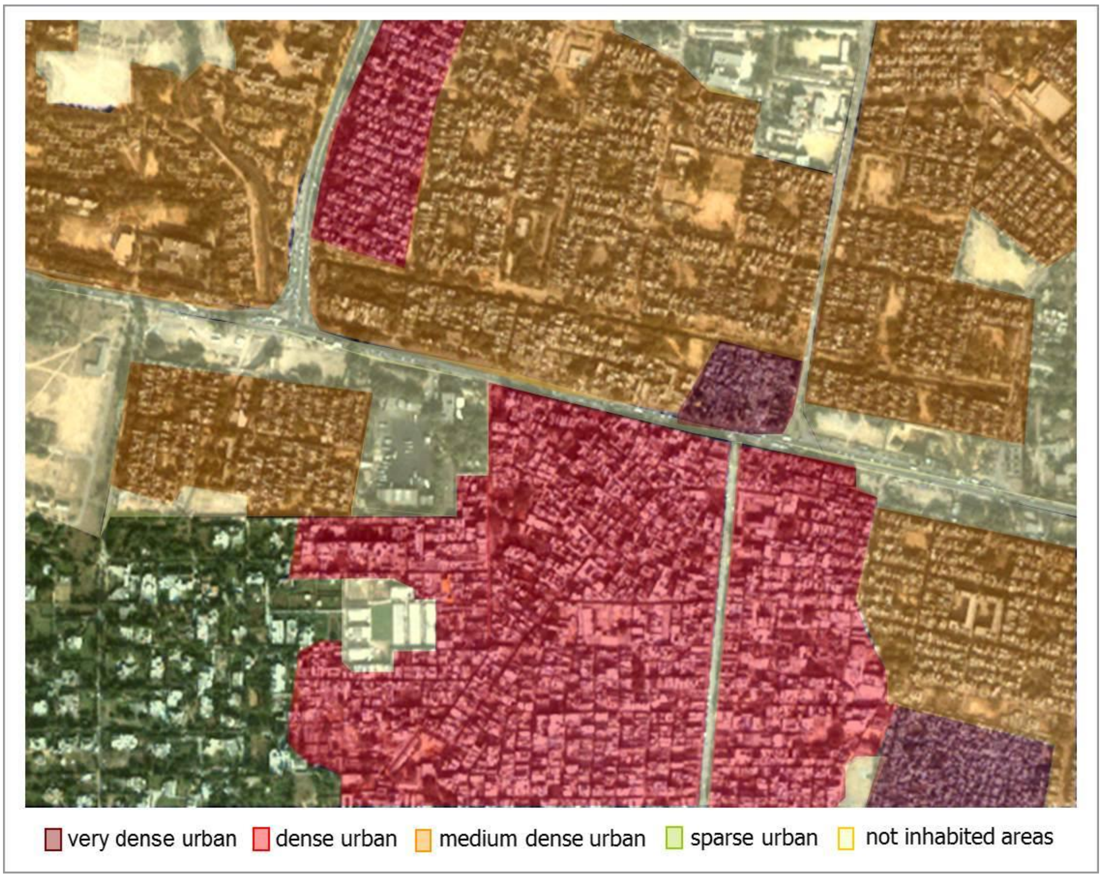


Figure 5-13: Density map of test site South s2 in the southern part of Delhi based on QuickBird scene South (12/18/2002) *(Data source: Digital Globe, draft: Susan Smollich).*

Combining the density maps (cf. Figure 5-12 and Figure 5-13) with the in-situ information (photographs etc., cf. Figure 5-11) and some first findings resulting from the household interviews, the following points can be stated:

1. Different settlement types show diverse spatial features — amongst others settlement density and settlement structure.

2. These settlement types can be assigned to different social classes, from the upper class over the middle-class to the lower class of residents.

3. The living conditions in the developed settlement types in Delhi vary very strongly. Everything could be observed from very poor to, for Indian conditions, very good living conditions. The living conditions are directly mirrored in the visible features of the settlements (e.g., building materials, mode of construction, and connection to infrastructure).

These general statements bear out the first basic assumption, which was made at the beginning of this thesis (cf. chapter 1.1), that the living conditions become apparent visually in the settlement structure. Up to this state of the study the satellite images were only used for purely visual interpretation. Based on this visual interpretation the conclusion was proved to be true that it is possible to suggest from the socio-economic data of a certain settlement area to its structure. The second and third working hypothesis (cf. chapter 1.1), which quote that different settlement structures are reflected and can therefore be identified and observed in the remote sensing data, will be examined in detail in the following chapters 6.1 and 7. Hence, the QuickBird data is subjected to a systematic image data analysis.

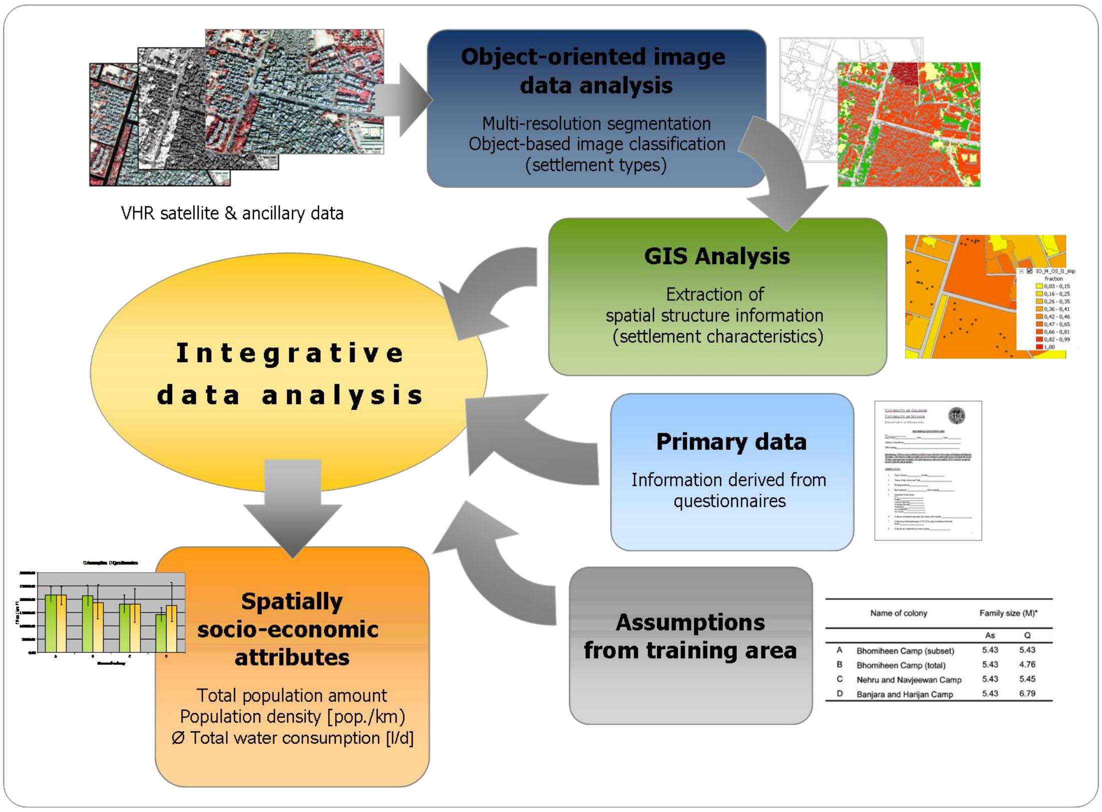
Chapter 6

Methodology and Conceptual Framework

This chapter presents an overview of the study workflow, starting with the segmentation of the QuickBird image data via the object-oriented classification of land cover, leading to the identification of informal settlements and other settlement types within the urban environment of Delhi and the derivation of information on population and water related parameters using an integrative data analysis. Focal point of this study is the integrative approach, which is used to investigate whether VHR remote sensing data can provide settlement characteristics (e.g., number of houses) in order to obtain — in combination with socio-economic data — different socio-economic attributes such as population amount, population density or water consumption. The conceptual framework of this study is shown in Figure 6-1.

6.1 Object-based Image Data Analysis

Very high-resolution (VHR) satellite images offer a great potential for the extraction of land cover and land use related information for urban areas. The available techniques are manifold (cf. chapter 3.2.2). In the past and until today the most common procedure to derive useful information from remotely sensed imagery has been pixel by pixel classification. An alternative way to look at image data is to divide the image into meaningful regions of similar pixels and to assign these so-called segments to land cover classes by any classifier. The conceptual idea of this promising and complementary approach is that each of these segments corresponds exactly to one and only one object class. This technique is named object-based image data analysis. After HAY & CASTILLA (2006) object-based image analysis (OBIA) is not only a technique to analyze remote sensing data, but also a sub-discipline of GIScience devoted to partitioning remote sensing imagery into meaningful image segments, and assessing their characteristics through spatial, spectral and temporal scale. OBIA requires, at its most fundamental level, image segmentation, attribution, classification and the ability to query and link individual segments in space and time.



	Name of colony	Family size (M)*	
		As	Q
A	Bhomiheen Camp (subset)	5.43	5.43
B	Bhomiheen Camp (total)	5.43	4.76
C	Nehru and Navjeewan Camp	5.43	5.45
D	Banjara and Harijan Camp	5.43	6.79

Figure 6-1: The conceptual framework of the study.

Mainly advances in computer technology and GIScience as well as a dramatic increase in commercially available high and very high-resolution remote sensing imagery in the first decade of the new century have led to the emerging field of OBIA (LANG & BLASCHKE 2006). The OBIA "movement" is also a response to increasingly affordable, available and powerful computing tools and a further development of object-oriented programming. Moreover, the recognition of limitations with pixel-based image approaches[11] (see also chapter 3.2.2) operates as a driver for an increasing use and further development of object-based classification techniques. Little by little the users are becoming more aware of the fact that

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[11] First and foremost, traditional pixel-based classifiers are disadvantageous due to the fact that pixels are not true geographical objects, the pixel topology is limited, and current remote sensing image analysis techniques mostly neglect texture, context and shape features. In addition, an increased variability implicit within VHR image data "confuses" pixel-by-pixel classifiers resulting in lower classification accuracies (HAY & CASTILLA 2006).

object-based techniques can make better use of neglected spatial information contained in remote sensing images, and provide greater integration with vector based GIS. Beyond that, analysts recognize that object-based methods are especially suited for multi-scale approaches in the monitoring, modeling and management of our environment, which, in turn, makes OBIA to a well established discipline.

Especially in terms of analyzing heterogeneous urban environments, including conceptual or spatial rules and conditions, a concept supported by object-based approaches is promising and needed. For that reason and because of the above mentioned drivers, also within this study an object-based image data analysis approach is applied in order to identify informal settlements and other settlement types within the urban environment of Delhi.

The objective of the following chapter is to provide an introduction into the subject *object-based image data analysis*. For that purpose, subchapter 6.1.1 describes the underlying concept of image segmentation. Within subchapter 6.1.2 the general principle of object-based classification is summarized.

Within this study, the software eCognition^{TM} (Professional 4.0), developed by the Definiens company (URL 18), is used for both image segmentation and classification. "The concept behind eCognition is that important semantic information necessary to interpret an image is not represented in single pixels, but in meaningful image objects and their mutual relationship" (BAATZ ET AL. 2003). The basic difference compared to pixel-based analysis techniques is that the software classifies image objects instead of single pixels. The image objects are extracted in a previous image segmentation procedure which uses a heuristic algorithm. To realize object-oriented classification, the eCognition technology includes moreover usual algorithms for image classification. The individual components and the analysis options of the software are explained in more detail and in a use-oriented way within the following chapters 6.1.1 and 6.1.2.

6.1.1 Creating Objects Using Image Segmentation

Performing object-oriented image data analysis in a common sense means to analyze the content of an image by analyzing image objects consisting of many pixels that have been grouped together by segmentation (ESCH ET AL. 2003, HAY & CASTILLA 2006). *Segmentation* represents the complete partitioning of an image into meaningful, non-overlapping regions (segments) based on one or more criteria of homogeneity.[12] in one or more dimensions of a feature space or on the differentiation to neighboring regions (heterogeneity), respectively

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[12] Homogeneity criteria for image segmentation are for instance texture, spectral signature or shape.

(HARALICK & SHAPIRO 1992, SCHIEWE 2002, LANG & BLASCHKE 2006). "Thus, segmentation methods follow the two strongly correlated principles of neighborhood and value similarity" (SCHIEWE 2002) and integrate therefore important features for image recognition, which are also of great importance in visual image interpretation (cf. chapter 3.2.2). This circumstance is expressed by TOBLER (1970) as *first law of geography*: "Everything is related to everything else, but near things are more related than distant things".

Image segmentation, which builds the basis of this classification approach, has been introduced already in the 1970ies and the 1980ies (HARALICK ET AL. 1973, HARALICK & SHAPIRO 1985, PAL & PAL 1993). The development of an image segmentation concept was mainly influenced by the work of HARALICK ET AL. (1973), where textural features based on gray-value spatial dependencies were used to classify images "on a block of contiguous resolution cells" (HURSKAINEN & PELLIKKA 2004). Image segmentation has been, and still is, an important research field within Pattern Recognition and Computer Vision and a multitude of segmentation algorithms have been developed during the past decades (HARALICK & SHAPIRO 1992).

Common segmentation methods are based on the following basic strategies for partitioning an image into meaningful regions, namely (1) point-based (e.g., grey-level thresholding), (2) edge-based (e.g., edge detection techniques), (3) region-based (e.g., region merging or growing and region splitting), and (4) combined (FU & MUI 1981, HURSKAINEN & PELLIKKA 2004, SCHIEWE 2002). Detailed explanations as well as mathematical basic principles and surveys of these algorithms can be found by HARALICK & SHAPIRO (1985, 1992), PAL & PAL (1993) as well as by MOREL & SOLIMINI (1995), GONZALEZ & WOODS (1993) and FREIXENET ET AL. (2002). However, SCHIEWE (2002) briefly describes the general concepts of image segmentation methods mentioned and emphasizes the particularities for the analysis of remotely sensed data.

Respective segmentation algorithms have been developed with successful and promising applications in various specific disciplines such as medicine or telecommunication engineering (SCHIEWE 2002, NEUBERT 2005). Except for the early research work of KETTIG & LANDGREBE (1976)[13], image segmentation was established rather late in remote sensing applications. The decelerated utilization of segmentation techniques in the field of remote sensing has been caused, amongst other things, by the complexity of the underlying object models and the heterogeneity of the sensor data in use. The application of these methods on spatially low- and medium-resolution remotely sensed data as well as on aerial photographs was limited to special purpose implementations only and has therefore not provided

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[13] KETTIG & LANDGREBE (1976) developed the system ECHO (Extraction and Classification of Homogeneous Objects), which is quoted in the literature as the first segmentation technique for the analysis of remotely sensed image data (SCHOWENGERDT 1997, NEUBERT 2005, NEUBERT ET AL. 2006).

significant improvements in image analysis. Moreover, the former poor development status of the methods as well as the limited computer technology were crucial obstacles for a general application of segmentation algorithms in the fields of remote sensing and photogrammetry (SCHIEWE 2002, NEUBERT & MEINEL 2003, NEUBERT 2005). Only recently and especially since the availability of VHR image data (cf. chapter 3.2.1) as well as due to the easier access to multi-source data sources, image segmentation techniques have been further and further developed and are nowadays increasingly used for remote sensing and thus for Earth observation applications. At last, significant progress in terms of user awareness was achieved with the advent of the first commercial and operational software product eCognition^{TM} in the year 2000 (SCHIEWE 2002, BAATZ & SCHÄPE 2000). Thenceforward, the interest in the remote sensing community has increased steadily and the number of segmentation-based image processing applications has grown considerably. In turn, this reorientation resulted in a permanent growing variety of implemented segmentation algorithms using very different concepts. Meanwhile a multitude of implemented segmentation algorithms in different software packages (e.g., ENVI, ERDAS) exist, which allow for an (semi-) automatic partitioning of remotely sensed image data. However, all segmentation algorithms have in common that they are providing the building blocks for any further object-based image analysis (HOFMANN ET AL. 2008). Altogether, this development is leading to a new object-oriented paradigm (NAVULUR 2007).

An application-oriented comparison as well as an assessment considering recently commercially distributed or for scientific use freely available segmentation algorithms based on real remote sensing image data is given in NEUBERT & MEINEL (2003), MEINEL & NEUBERT (2004), and NEUBERT ET AL. (2006) as well as in NEUBERT ET AL. (2008) and NEUBERT & HEROLD (2008) . In these studies, the partly very different characteristics of the available segmentation programmes are shown and diverse capabilities are presented.

Image segmentation represents the interface between image pre-processing and classification. Thus, "image segmentation is a crucial step within the object-oriented remote sensing information retrieval process" (NEUBERT & MEINEL 2008). Since the classification process is based on the segment properties generated (e.g., spectral mean, shape etc.), a substandard segmentation quality has an adverse effect on the classification quality. Hence, the success of object-oriented image classification approaches, i.e. the assignment of the generated image segments to classes which are described by rule bases depending on the segments' properties, is directly affected by the quality of the segmentation results. As a rough rule of thumb it can be stated that, the better the generated segments are capable to represent the imaged objects in the image data, the better the quality of the segmentation process and consequently the classification results are. (HOFMANN ET AL. 2008). The quality assessment of image segmentation results is therefore "of fundamental significance for the recognition process as well as for choosing the appropriate approach and parameters for a given segmentation task" (NEUBERT & MEINEL 2008). In order to perform a quality assessment of segmentation results using different algorithms and modified parameters, NEUBERT & MEINEL (e.g., 2008) proposed for instance to compare segmented objects with reference objects using formal characteristics only.

Figure 6-2: Representation of a real-world object in image data of different spatial resolution *(Source: modified after HOFMANN ET AL. 2008).*

Image segmentation has to generate meaningful objects (e.g., streets, buildings), which represent real world objects of interest. In this regard, it is evident that the ability of the segments to represent real world objects in image data is on the one hand strongly dependent on the properties and quality of the image data used. Thereby, the ability mainly depends on the spatial resolution of the image data (cf. Figure 6-2). Disturbing factors can be fuzziness, absence of contrast, atmospheric effects, shadows, too far off-nadir viewing angles or overlap (cf. chapter 3.2.2). Imprecise representation of the real world objects may originate on the other hand from the selected segmentation approach itself. Thereby, the used segmentation method as well as the used homogeneity value and its parameterization are primarily of importance. Moreover, the transferability of the segmentation methods as well as the accurate repeatability of the segmentation process is a crucial precondition. A further aspect that needs to be taken into account is the independency of the segmentation results of the chosen starting points (HOFMANN ET AL. 2008, NEUBERT 2005). A detailed survey of the requirements on a successful segmentation is provided for instance by GORTE (1999) and HALLE (1999).

As previously stated, in this study a so called multi-resolution segmentation (MRS), implemented in the eCognition^{TM} software (BAATZ ET AL. 2003), has been applied for object delineation. This segmentation algorithm is based on a region-growing approach where pixels are iteratively grouped into objects based on predefined similarity criteria. Since recently, region-growing methods have most commonly been applied to the analysis of remote sensing data. More examples of region-growing approaches can be found by EVANS ET AL. (2002) and TILTON (1998). The MRS procedure detects local contrasts and was especially developed to work even on highly textured data, such as VHR imagery. Furthermore it allows the segmentation of an image into a network of homogeneous image objects at any chosen resolution (fine or coarse structures). The object's attributes can then be used for subsequent classification (BAATZ ET AL. 2003).

The MRS technique extracts image objects at modifiable

- *Homogeneity criterion*, which is represented by the two parameters *color* (spectral properties) and *shape* (spatial properties) (cf. Equation 6-1). In this context homogeneity is used as a synonym for minimized heterogeneity. With the color/shape weighting factor the influence of color vs. shape homogeneity on the object generation can be adjusted. The color parameter defines the overall contribution of spectral values in regard to homogeneity. Thereby, the sum of the standard deviations of spectral values in each layer weighted with the weights for each layer is used (cf. Equation 6-2). The lower the color criterion is, the less spectral values of the image layers contribute to the entire homogeneity criterion and thus to the object generation. The shape criterion (cf. Equation 6-3) is defined by two sub-parameters: *smoothness* and *compactness*. The smoothness factor describes the ratio of the de facto border length of an object to the shortest possible border length given by the rectangle along the grid which contains the object (cf. Equation 6-4). The compactness factor describes the ratio of the de facto border length and the square root of the number of pixels forming this image segment (cf. Equation 6-5). The smoothness factor can be used to optimize image objects for smoother boarders, whereas the compactness factor especially helps to avoid a fragmented shaping of objects. The shape criterion in general helps to avoid a fractal shaping of objects. This fact applies primarily to strongly textured data, such as radar images (HOFMANN 2001a, HOFMANN ET AL. 2008, BAATZ ET AL. 2003, NAVULUR 2007, DE KOK 2001, FRAUMAN & WOLFF 2005). Figure 6-3 shows the segmentation dialog window in which the parameter input is carried out manually.

$$f = w \cdot h_{color} + (1 - w) \cdot h_{shape}$$

Equation 6-1

f = homogeneity criterion

w = user defined weighting factor for color (against shape) with $0 \leq w \leq 1$

h_{color} = homogeneity of color

h_{shape} = homogeneity of shape

$$h_{color} = \sum_{c=1}^{n} (w_c \cdot \sigma_c)$$

Equation 6-2

h_{color} = homogeneity of color

w_c = weighting of layer c of an image

σ_c = standard deviation of layer c of the pixels of a segment

$$h_{shape} = w_{compact} \cdot h_{compact} + \left(1 - w_{compact}\right) \cdot h_{smooth}$$

Equation 6-3

h_{shape} = homogeneity of shape
$w_{compact}$ = weighting with $0 \leq w \leq 1$
$h_{compact}$ = homogeneity of compactness
h_{smooth} = homogeneity of smoothness

$$h_{smooth} = l/b$$

Equation 6-4

h_{smooth} = homogeneity of smoothness
l = length of the borderline of a segment/ object perimeter
b = length of the borderline of the minimum surrounding rectangle of segment

$$h_{compact} = l/\sqrt{s}$$

Equation 6-5

$h_{compact}$ = homogeneity of compactness
l = length of the borderline of a segment / object perimeter
s = size of a segment measured in number of pixels

- *Scale* parameter, which indirectly influences the average object size. The scale parameter operates as a boundary value within the segmentation process representing the maximum allowed value of the homogeneity criterion during the fusion of two pixels or segments respectively (cf. Equation 6-6). In fact, this parameter determines at the same time the maximum allowed heterogeneity of the resulting object. Thereby, it represents the termination criterion of the segmentation process. "For a given scale parameter, heterogeneous regions in an image will result in a fewer number of objects as compared to homogeneous regions" (NAVULUR 2007). The size of image objects can thus be varied by modifying the scale parameter value. Hence, a larger scale parameter value leads to bigger objects and vice versa.

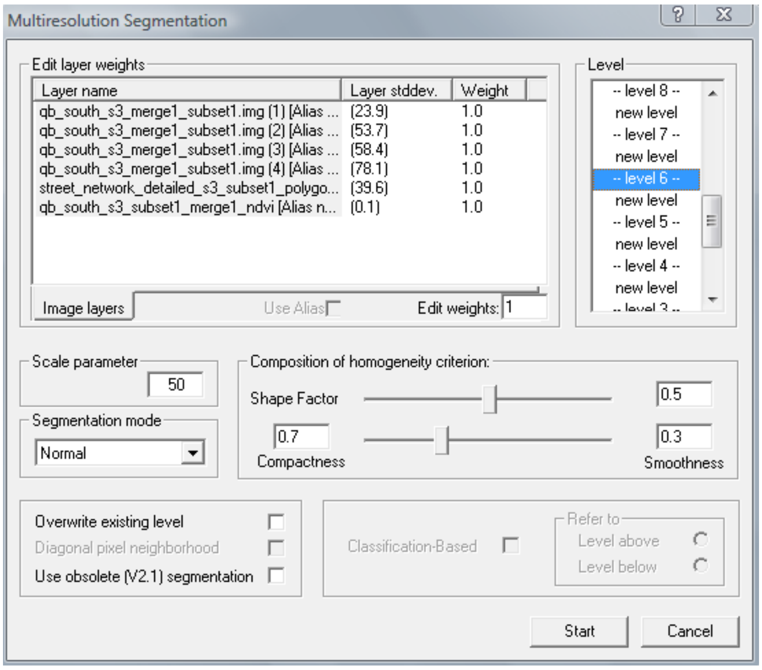
$$SP \geq \sqrt{f}$$

Equation 6-6

SP = scale parameter
f = homogeneity criterion

- *Level*, whereas this criterion controls whether a newly generated image level will either overwrite a current level or whether the generated objects shall become sub- or super-objects of a still existing level. The order of generating the levels affects the shape of the objects (top-down vs. bottom-up segmentation).
- *Single layer weight*, which can be used to more or less weight the impact of the channels on the object generation.

Further parameters can additionally be selected in the segmentation dialog window, such as the segmentation mode (normal, sub-object line analysis or spectral difference) or the utilization of the geometry of thematically ancillary data as well as the provision for diagonal pixel neighborhood (cf. Figure 6-3).



Layer name	Layer stddev.	Weight
qb_south_s3_merge1_subset1.img (1) [Alias ...	(23.9)	1.0
qb_south_s3_merge1_subset1.img (2) [Alias ...	(53.7)	1.0
qb_south_s3_merge1_subset1.img (3) [Alias ...	(58.4)	1.0
qb_south_s3_merge1_subset1.img (4) [Alias ...	(78.1)	1.0
street_network_detailed_s3_subset1_polygo...	(39.6)	1.0
qb_south_s3_subset1_merge1_ndvi [Alias n...	(0.1)	1.0

Use Alias ☐
Edit weights: 1

Level:
-- level 8 --
new level
-- level 7 --
new level
-- level 6 --
new level
-- level 5 --
new level
-- level 4 --
new level
-- level 3 --

Scale parameter: 50
Segmentation mode: Normal
Composition of homogeneity criterion:
Shape Factor: 0.5
Compactness: 0.7
Smoothness: 0.3

Overwrite existing level ☐
Diagonal pixel neighborhood ☐
Use obsolete (V2.1) segmentation ☐
Classification-Based ☐
Refer to
Level above ○
Level below ○

Figure 6-3: Dialog window for manual input of the segmentation parameters in eCognition^{TM} 4.0. Further explanations are included in the text.

Understanding the effects of each of these criteria is necessary to segment an image and create homogeneous objects at any chosen resolution for a given application (NAVULUR 2007). Please see the eCognition User Guide (BAATZ ET AL. 2003) for further information on the science behind the single criteria. In the following section and in chapter 7.1, where the segmentation results are presented, the effects of combining and modifying these four parameters on creating varying image primitives will be shown.

As mentioned before, the image objects created by the initial segmentation should best suit the image analysis purposes, i.e. the image segmentation should provide image objects which best suit the ontology of the desired classes (JAIN ET AL. 2005). Finding the appropriate parameter settings to obtain a satisfactory segmentation result depends on both the nature of the imagery (spatial resolution, spectral properties, number of image channels etc.) and the nature and complexity of the objects to be detected (YUSOF ET AL. 2008). For this reason a universally valid statement concerning the parameter selection is not possible. Before the segmentation process is executed, it is therefore essential that the user is aware of the character and size of the required image objects primitives. The decisions taken at this stage are fundamental and will always have influence on the final result. It is common practice that people individually adopt the segmentation parameters in order to obtain the best possible object delineation for each land cover class. The correct settings are therefore usually determined experimentally, by a process of trial and error based on visual observation or estimated values. This procedure is very time-consuming and a transfer to other test sites or images is difficult or even impossible (YUSOF ET AL. 2008, DE KOK 2001). How much the generated segments can differ from each other using different parameter settings is illustrated in Figure 6-4 and Figure 6.5.

Figure 6-4: Effect of different scale parameter settings: 1 — basis data, 2 — scale 50, 3 — scale 100, 4 — scale 125; constant parameters: shape [0.5], color [0.5], smoothness [0.3], and compactness [0.7]. Blue lines delineate the image objects. The yellow marked object represents the reference object. The QuickBird image (basis data) is displayed as false color composite 4/3/2. Further explanations are included in the text.

Figure 6-4 illustrates the direct influence of the scale parameter upon the segment size and the analyzing possibilities accordingly. With a smaller scale parameter (Figure 6-4 [2]) the green space (yellow marked segment) is clearly separated from the surrounding, without comprising other land cover classes. This means that the scale value would be particularly applicable for the classification of vegetation areas. Applying a higher scale value (Figure 6-4 [3]) other classes may already be comprised in the segmented object (under segmentation). The segmentation results of this run would only be useable for a subsequent qualitatively exact classification with intensive manual efforts. Within Figure 6-4 [4] a complete block of buildings (yellow marked object) is segmented out of an image which comprises a multitude of different classes (e.g., vegetation, impervious, shadow). Hence, this segmentation level would be particularly applicable for a classification where the major task is the identification of different settlement types.

Figure 6-5 shows firstly the results of a segmentation, where only the spectral information (color = 0.9, shape = 0.1) is considered and secondly the results of a segmentation where only the shape parameter (color = 0.1, shape = 0.9) is considered to demonstrate the influence of these two parameters regarding the segmentation results. The upper illustrations (Figure 6-5 [2] to [4]) show the results of the segmentation with maximum weighting of the color parameter, whereas the lower illustrations (Figure 6-5 [5] to [7]) show the results of the segmentation with maximum weighting on the shape parameter (with constant values for compactness and smoothness in both cases). The illustrations show a well visible discrepancy within the segmentation outcomes. The solely utilization of the color parameter leads to homogeneous areas in terms of color, but the areas are oversegmented (e.g., Figure 6-5 [2]). The maximum weighting of the shape parameter on the other hand delivers an undersegmentation that is mostly unusable for further classification purposes as the color information of the objects is ignored.

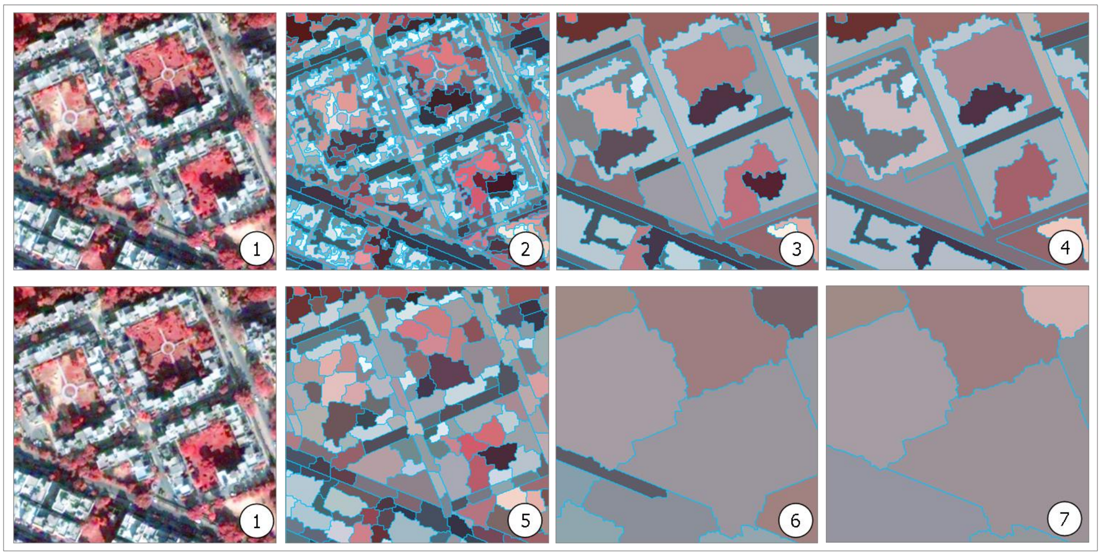


Figure 6-5: Composition of homogeneity criterion: varied weighting of shape and color parameters: 1 — basis data, 2 — color [0.9], scale 25; 3 — color [0.9], scale 100; 4 — color [0.9], scale 150; 5 — color [0.1], scale 25; 6 — color [0.1], scale 100; 7 — color [0.1], scale 150; constant segmentation parameters: smoothness [0.5], and compactness [0.5]. Blue lines delineate the image objects. The QuickBird image (basis data) is displayed as false color composite 4/3/2. Further explanations are included in the text.

Hence, for the selection of adequate segmentation parameters only relatively general rules of thumb can be established. In order to generate meaningful objects for the question of interest, the segment dimensions should be chosen neither too large (undersegmentation) nor too small (oversegmentation). Moreover, an as low as possible number of the image objects should be composed of not more than one of the classes of interest (endmember). The segment size is mostly smaller than the one of the region of interest. If necessary, too small objects can be remerged using the function *classification-based segmentation*[14].

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[14] The function classification-based segmentation was not applied within this study because of the desired transferability and automation of the developed approach.

In this research a sensitivity study for searching suitable segmentation parameters was as well carried out manually. After examining numerous segmentations with different scale parameters and homogeneity criteria (shape and color) and visually comparing these with the original QuickBird image, the segmentation parameters were chosen based on how clearly and accurately the segments delineated the boundaries of the small (single residential buildings) and large objects (e.g., green and open spaces as well as settlements itself) visible in the image. In the following, these parameters were fixed and were applied for each test site. The shape and color parameters were weighted equally, whereas the compactness was prioritized instead of smoothness. Finally, the scale parameter was changed systematically, while the residual homogeneity parameters and the layer weights remained constant (cf. Table 6-1). This strategy makes the approach itself as well as a subsequent transfer faster, transparent and more robust.

Table 6-1: Segmentation parameter settings

Level	**Scale**	**Color**	**Shape**	**Shape settings**	
				Smoothness	Compactness
1	5	0.5	0.5	0.3	0.7
2	10	0.5	0.5	0.3	0.7
3	15	0.5	0.5	0.3	0.7
4	20	0.5	0.5	0.3	0.7
5	25	0.5	0.5	0.3	0.7
6	50	0.5	0.5	0.3	0.7
7	75	0.5	0.5	0.3	0.7
8	100	0.5	0.5	0.3	0.7
9	125	0.5	0.5	0.3	0.7
10	150	0.5	0.5	0.3	0.7
11	175	0.5	0.5	0.3	0.7
12	200	0.5	0.5	0.3	0.7

After the determination of appropriate values, the parameters should be selected within the first segmentation step in a way that the smallest segments required are generated. Within a subsequent segmentation process on a higher level not the computationally intensive pixel level is used, but only the directly underlying segmentation level is considered. As the segmentation process is a very time consuming procedure, which requires an extensive computation capacity, it is generally recommendable to initially apply test runs to image subsets which are representative for the whole scene (cf. chapter 5.1).

The image segments have to be calculated on several hierarchical levels following an iterative process (YUAN & BAUER 2006). As an "ideal" object scale does not exist – because of the heterogeneity within the images –, objects of different levels of segmentation (spatial) and of different meanings (thematic) have to be combined.

In this regard, streets often form a natural boundary between different settlements. Therefore an extraction of the main roads is useful to separate different settlements. As the road surfaces in Delhi are very inhomogeneous, which means that different materials alternate within single roads, the creation of a manually generated street layer based on the QuickBird data was necessary (cf. Figure 6-6 [3]). It could be found out by examination that a segmentation embedding a street layer provides better results for the separation of adjacent settlements of different types. Alternatively digital street maps of the representative city area could use here. Moreover, the NDVI (Normalized Difference Vegetation Index) (MYNENI ET AL. 1995) was included as an additional band for both image segmentation and classification (cf. Figure 6-6 [2]). On the basis of the NDVI a separation of vegetation covered and vegetation less areas as well as a masking of the vegetation within the image is easier. These additional data, in turn, enable an optimization of the segmentation and therefore of the image classification.

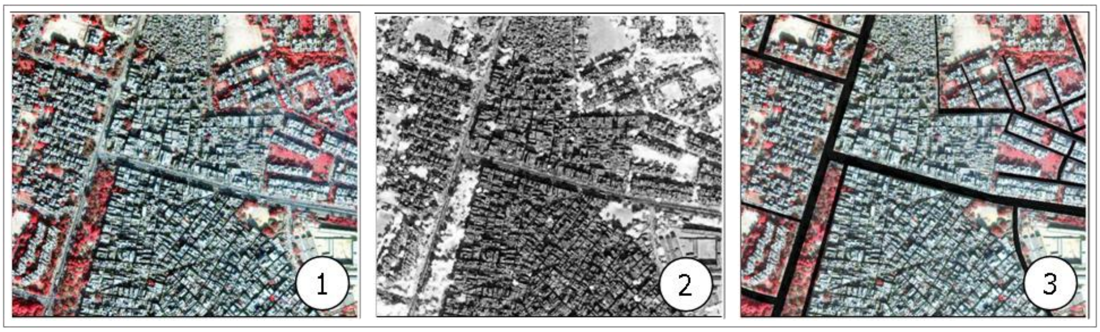

Figure 6-6: Raw data for multi-resolution image segmentation: 1 — training area test site South s3 (channels 4, 3, 2), 2 — NDVI image, and 3 — street layer (manually generated).

The processing within the eCognition^{TM} software is structured strictly hierarchically. The ability to segment on different levels allows for the generation of different object sizes within one and the same segmentation process (cf. Figure 6-7). This, in turn, provides the opportunity — comparable to the human ability of recognition — to identify different object sizes simultaneously. The pixels of the lowest level are merged to segments within the next higher level. Hence, the first segmentation step provides homogeneous object primitives according to the homogeneity criterion. With subsequent segmentation steps within the next higher levels these object primitives can be amalgamated to bigger objects — given the fact that they are no sub-objects of different super-objects (bottom-up approach). A top-down[15] segmentation and an integration of levels between already existing levels is possible as well if the above mentioned preconditions are fulfilled. Hereby, the border lines of the segments

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[15] A top-down segmentation requires a significantly longer computation time, because the segmentation of each level is computed considering pixel values.

are congruent. In case the analyst has assigned features to the image objects, these will always be bequeathed to next higher object level (NEUBERT 2005, HOFMANN 2001b).

As informal settlements are the main issue of this research, the segmentation procedure was developed with the focus on a classification of this specific settlement structure. Due to the ambition to classify other settlement structures subsequently as well, these were kept in mind during the development of the segmentation process.

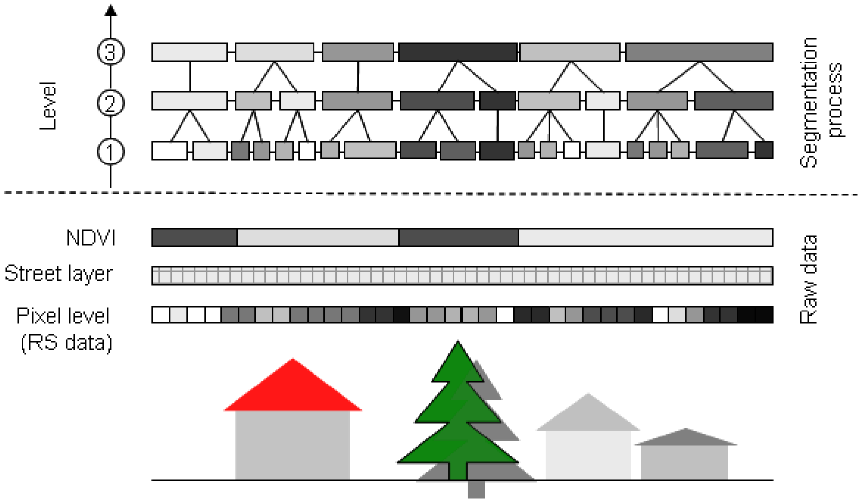

Figure 6-7: Hierarchical network of image objects — result of multi-resolution image segmentation: "bottom-up" approach (abstract illustration) *(Source: BAATZ ET AL. 2003, modified)*.

For the detection of different settlement types textural information is essential. Particularly for informal settlements the image texture is highly variable at different scales (HOFMANN 2001a). Thus, in this study a *bottom-up* approach with very fine segmentation on the base level (level 1, very small objects) and a coarse segmentation on the top level (level 12, large objects) was applied (cf. Figure 6-7 and Table 6-1). That means that altogether 12 levels were calculated where level 1 represents the smallest objects and level 12 represents the biggest objects of the segmentation. To take advantage of the textural information, objects on the top level outline more or less different settlement areas and other objects of comparable size (e.g., industrial areas, large unimproved areas). Intermediary segmentation levels are necessary for the identification of medium scale objects (smaller settlement areas, large buildings, open and green spaces etc.). The base level (1) holds image objects which coincide with the smallest residential buildings, as well as with small road segments and small vegetation areas. In principle, this makes it possible to describe later on spatial relationships between e.g., settlement areas and small residential buildings as well as neighborhood relations reflecting aspects of segregation (JAIN ET AL. 2005).

Hence, the segmentation results in a hierarchical network of image objects (cf. Figure 6-7), whereas each segment is connected to its vertical and horizontal neighbors (ESCH ET AL. 2003). This means that each segment "knows" its context, its neighborhood as well as its sub- and super-object respectively. These object relations and context information respectively are explicitly utilizable for the classification process. The hierarchical network of image segments provides possibilities for innovative data analysis. Thus, structures of different scales can be on the one hand represented simultaneously and therefore classified in relation to each other. One the other hand, different hierarchical levels can be segmented based on different underlying data (layer). In addition, the shape of image objects can be corrected based on a regrouping of sub-objects. The analysis of image objects based on sub-objects is a powerful tool, which offers the possibility to realize texture analyses. Attributes for the classification of all sub-objects of an image object can be for instance contrast or shape. Another possible application of the hierarchical network of image objects is the classification of image objects in relation to their respective super-objects (BAATZ ET AL. 2003, BAATZ & MIMLER 2002).

6.1.2 Object-oriented Image Classification Approach

Usually classifying means assigning a number of pixels or objects to a certain land cover or land use class according to the description of the typical properties the classes of interest have. The pixels and objects then become assigned whether they do or do not satisfy these properties. A class definition always contains uncertainties and can never be absolute. In general, classifiers in remote sensing are therefore subdivided in *hard* and *soft* (also known as *fuzzy*) classifiers. While hard classifiers (e.g., maximum-likelihood, minimum-distance) assign a membership of 1 ("yes") or 0 ("no") to the objects, expressing whether an object belongs to a certain class or not, soft classifiers use a contiguous range of membership to express an object's assignment to a class. Thereby the membership value usually lies between 1.0 and 0.0, where 1.0 means a complete assignment ("exactly yes") and 0.0 means absolute improbability ("exactly no"). In other words, all values between 0 and 1 represent a more or less certain state of "yes" and "no". The degree of membership depends on the degree to which the objects fulfill the class-describing properties (BAATZ ET AL. 2003, NEUBERT 2005). With respect to image understanding, classification results based on soft methods are "more capable of expressing uncertain human knowledge about the world and thus lead to classification results which are closer to" (BAATZ ET AL. 2003) human visual interpretation. Moreover, an advantage of soft classifiers lies in their possibility to express each object's membership in more than just one class as well as to express uncertainties about the classes' descriptions. The most powerful soft classifiers are fuzzy systems. Three main work steps comprise a fuzzy system, namely (1) the *fuzzification* of input variables, which results in fuzzy sets, (2) the *fuzzy rule base* and (3) the *defuzzification*. For a detailed description of these terms and fuzzy logic in general see for instance BOTHE (1993), BENZ ET AL. (2004), BAATZ ET AL. (2003), YAGER ET AL. (1987) or ZADEH (1965 and 1973).

In this study, starting with the segments generated as explained above, a classification method was developed and conducted to detect and differentiate settlement types within the urban area of Delhi. A multi-level fuzzy logic rule base to classify image objects was used (BAATZ ET AL. 2003) which combines intrinsic features (physical properties of objects like color, texture and form), topological features (geometric relationships between the objects or the whole scene) as well as contextual features (features which describe the semantic relationships of objects) on different levels. For this purpose, two basic classification algorithms are implemented in eCognition^{TM}: (1) a traditional nearest neighbor (NN) classifier and (2) a fuzzy membership function approach. Both serve as class descriptors and can be used in combination. Using a NN classifier the analyst interactively collects sample objects for each class of interest from the image to train the classifier. In contrast, fuzzy membership functions describe the intervals of feature characteristics wherein the objects do belong to a certain class or not by a certain degree (see section above) (DARWISH ET AL. 2003, HURSKAINEN & PELIKKA 2001, HOFMANN 2001a, YUSOF ET AL. 2008). Both classifiers are based on the so called *class hierarchy* — a framework that comprehends all the classes of the classification scheme and allows for a hierarchical organization of the image objects. A class hierarchy in eCognition^{TM} can be moreover understood as a rule base wherein the analyst determines physical and semantic properties typical for the objects of a certain class (cf. Figure 6-10) (HOFMANN 2001a, YUSOF ET AL. 2008).

While analyzing the different characteristics of the objects obtained by the segmentation, such as reflectance, texture, shape or size, the user has the ability to determine which features and which range of their values shall be used to amalgamate objects into the same class or otherwise to allocate them into separate classes (YUSOF ET AL. 2008). Thus, the user has to be aware of disjunctive properties for each class of interest, which in certain cases might require appropriate a-priori and/or in-situ information respectively (HOFMANN 2001b). A key issue of the rule base development is therefore the selection and subsequent use of robust features for the class description. The eCognition^{TM} software provides a large amount of features which can be used by means of fuzzy logic to build class descriptions. The software distinguishes in total three groups with more than 70 features which can be used for classification: *object features*, *class-related features* as well as *terms* (cf. BAATZ ET AL. 2003). Dealing with image objects instead of single pixels, the group of object features includes, besides spectral statistics (e.g., mean, standard deviation, ratio), shape and neighborhood information usable in the classification process, which are not available in the pixel-based fuzzy classifier (SHACKELFORD & DAVIS 2003). In addition, amongst others, textural features such as Haralick parameters (HARALICK ET AL. 1973) in each object can be calculated.

The crux of this classification therefore lies in the selection of the above mentioned features and the determination of the appropriate settings, which make it possible to differentiate between different settlement structures as well as land cover classes. Thus, *feature recognition* is a complex and decisive part of object-oriented, rule-based image analysis. Given the enormous number of possible features for object description, it is necessary to identify the characteristic, significant and robust features for object classes of interest. Therefore, a comprehensive feature selection methodology is the precondition for successful processing of image objects. After Nussbaum & Menz (2008) a good feature analysis is a consistent technique that "should be able to analyze a large number of features, it should identify the characteristic features for any number of object classes and it should, moreover, determine the thresholds for the feature intensity which achieves optimum separation from the other object classes". In addition, the methodology should also allow a comparison of their suitability (Nussbaum et al. 2006). Recently there exists a large variety of feature selection algorithms (e.g., Carleer & Wolff 2006, Nussbaum & Menz 2008). Feature selection in general is a process commonly used in *machine learning*. Machine learning refers to algorithms which analyze the information, recognize patterns, and improve prediction accuracy through repeated learning from a set of representative training instances (De Fries & Cheung-Wai Chan 2000, Canty 2006, and Bishop 2006). Broadly speaking, machine learning involves tasks for which there is no known direct method to compute a desired output from a set of inputs. Both supervised as well as unsupervised classification algorithms for remote sensing imagery belong to machine learning techniques (Canty 2006).

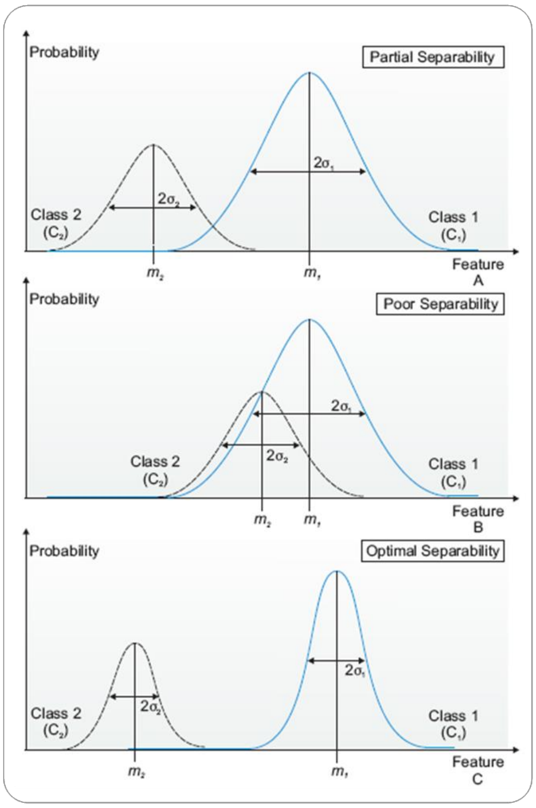

Figure 6-8: Examples of probability distributions *(Source: Nussbaum et al. 2006).*

In the present study an automatic feature extraction methodology, called *SEaTH* (SEparability and THresholds) (Nussbaum et al. 2005, 2006, and Nussbaum & Menz 2008), is used for seeking significant features for optimal class separation. SEaTH calculates the separability and the corresponding thresholds for every object class and object class combination as well as for any number of given features with a statistical approach based on a set of training data. The choice of training data in SEaTH is similar to the selection of training areas for supervised classification of remote sensing imagery. But instead of a training data set consisting of labeled pixels, groups of pixels (image objects) are involved as representatives of each land cover class of interest. The analyst has to select representative image objects for each of the classes of interest by visual examination of the image data (Canty 2006). Thus, the chosen training objects represent a small number out of the total amount of generated image objects. The identification of the significant features is "a problem of probability density estimation" (Nussbaum et al. 2006). In SEaTH, on the basis of the representative training objects for each land cover class, the probability distribution for each class is therefore estimated and used to calculate the separability between two land cover classes (cf. Figure 6-8). Hence, the statistical measure for determining the representative features of each object class is the mutual separability of the object classes. Suitable measures for separability are for instance the *Bhattacharyya distance* (Bhattacharyya 1943, Fukunaga 1990) or the *Jeffries-Matusita distance* (Nussbaum et al. 2006), whereas the last one is a more useful measure for separation in classification contexts since it has a finite dynamic range. After determining adequate features, separating the object classes in an optimal way, the decision-threshold for maximum separability has to be calculated. "The knowledge of the optimum threshold is necessary for the assembly of a ruled-based classification model" (Nussbaum et al. 2006). SEaTH provides a Gaussian probability mixture model for the calculation of an ideal threshold. An example probability distribution of two classes can be observed inFigure 6-9. Subsequently, SEaTH calculates those thresholds which allow the maximum separability in the selected features depending on the respective segmentation level. Thresholds obtained in this manner are then used to separate different classes in the image classification process. Finally, the results of SEaTH are presented in tables, where an interpretation of the results allows a quick preparation of a classification model, with statistically optimized features and thresholds (Nussbaum et al. 2006). Detailed explanations, mathematical basics as well as validation results of the SEaTH methodology can be found at Nussbaum et al. (2006), Nussbaum & Menz (2008), and Marpu et al. (2006).

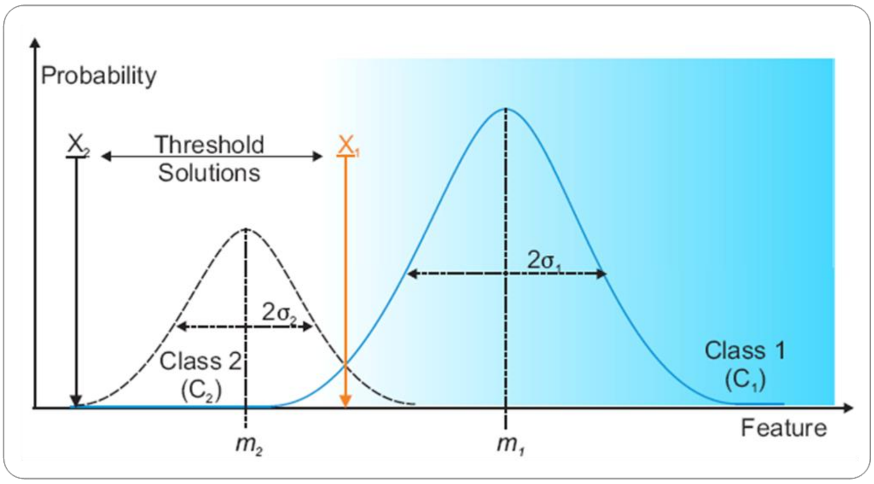

Figure 6-9: Threshold identification used within the automatic feature extraction methodology SEaTH *(Source: Nussbaum et al. 2006).*

A further aspect that has to be taken into account at this stage is the transferability of the analysis methods used. The development of a rule base requires not negligible efforts. A rule base is the more transferable, the less it needs to be manually adapted to the specific image characteristics. Therefore, during the development of a rule base, it should be avoided to formulate rules, which are too dependent on the image data, which in term would diminish the transferability. A rule base should be designed in a way that it depends only on image independent object features at a first stage and at a second stage on features, which can easily be adapted to differing imaging conditions (HOFMANN ET AL. 2008). Moreover, given the premise of transferability, properties with attributes which are as stable as possible in terms of time and space should be considered. This aspect has as well been taken into account during the development of the present method. In general, different settlement types differ mainly in building size and their density or sealing degree respectively, as well as in used building materials, visible structure and fraction of vegetation (cf. chapter 4.1 and 4.2). This means that both spectral and textural properties as well as contextual features are suitable to describe and identify different settlement types. Textural and contextual properties are, however, because of their robustness and transferability, better suited to describe different settlement types than spectral properties (HOFMANN 2001b, ESCH & ROTH 2004) — at least if the analyst wishes to classify settlement types with similarly observable characteristics in different areas or based on different image data. In the opinion of some authors (e.g., HOFMANN 2001b, HOFMANN ET AL. 2008, ESCH & ROTH 2004) spectral features are too susceptible to describe settlement areas or urban areas (in general) respectively, unless one is dealing with very constant parameters such as the NDVI, which can be easily adapted to differing imaging conditions.

Since informal settlements represent, in general as well as in the city of Delhi in particular, the most visible expression of urban poverty, the main emphasis of this analysis is put on the identification and analysis of this settlement type. Accordingly the classification procedure of this settlement type is described here in more detail. The features "high building density" and "small building size" as well as "complex shape appearance to the outside and high heterogeneity within the settlement" were found to be the most important characteristics to identify informal settlements from the VHR image data (cf. chapter 2.4 and 4.2). Basically, these features are implemented in the classification algorithm in terms of texture parameters. All features concerning texture are based on sub-object analysis. Therefore, the object class "informal settlement" is not classified in the level in which it is entirely included, but in a smaller level with corresponding sub-objects (cf. next section). In general the textural features are divided into two groups: texture concerning the spectral information of the sub-objects and texture concerning the form of the sub-objects. In case of the identification of informal settlements the spectral information is determining. For instance HOFMANN (2001b) uses spectral texture properties as well as prime criteria for informal settlement detection. Thus, applying the SEaTH methodology, the texture parameters after Haralick[16] (HARALICK 1979 and HARALICK ET AL. 1973) could be determined as valuable features and could be afterwards applied successfully in eCognition™ for the identification of informal settlements. Particularly the parameters *GLCM - Angular Second Moment*[17] and *GLCM – Entropy*[18] were implemented in this analysis (cf. Figure 6-10 and Table 6-2). Since not all very dense areas in Delhi are informal settlements, the term "very dense urban area" was chosen for demonstration purposes of that settlement type. The impervious surfaces, situated outside of the objects declared as "very dense urban", were identified applying the textural parameter *GLCM – Contrast*[19]. For the extraction of the remaining land cover classes, spectral layer value features were applied. Whereas, as expected, the *mean* of the accessory NDVI band operates as most useful feature for the identification of vegetation areas (cf. Figure 6-10), the features *mean difference to neighbors* and *mean* are used for shadow classification. The class "streets" is simply described by *mean*, *ratio* and *relative border to brighter neighbors* in the self generated street layer (cf. Table 6-2). The residual objects are assigned to the class "background" automatically, which is synonymous with the land cover class "not impervious".

Another challenge of the approach is based on the fact that the different classes and structures need to be classified in different segmentation levels since each level provides, due to different object sizes, disparate information about spectral and textural content. While a bottom-up approach — from the smallest unit pixel to the largest segments in level x — forms the basis of the segmentation process, an exactly contrary principle — a *top-down* approach — is implemented for the present classification procedure (cf. Figure 6-11). Consequently, the image segments are classified contrarily to their segmentation sequence, this means from the coarse, individually defined level x to the fine levels (e.g., level x-i with i=1, …, x). All generated segmentation levels down to the base level are available for the thematic classification process. The object-oriented, hierarchical classification procedure is thus based on x levels resulting from the segmentation process (TAUBENBÖCK 2007). Hereby

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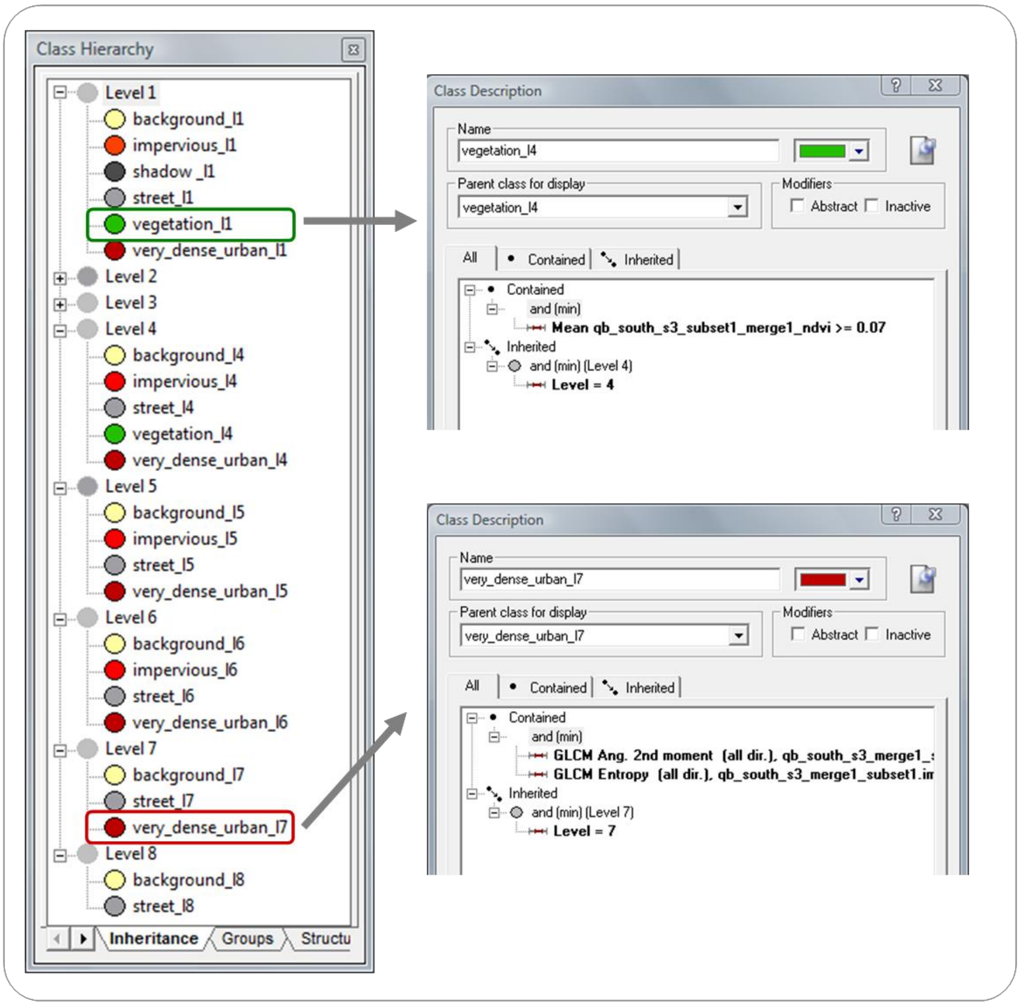
[16] HARALICK ET AL. are using a so-called *Grey-Level Co-occurrence Matrix* (GLCM) for derivation of statistics of second order in digital images. A GLCM is a matrix derived from the grey level image, which shows the joint-probability of distribution of a pair of grey levels, separated at a certain distance and a certain orientation (ZHANG ET AL. 2003). A GLCM is the appraisal of the probability of the transition from grey scale level i to grey scale level j of two neighboring picture elements, whereas the neighborhood is defined by a transition vector. Second order statistical parameters with the application of GLCMs are considering as well the spectral as the spatial distribution of the grey scale values. So-called textural features are being derived from GLCMs, which represent the characterization of the GLCM within a single value (HARALICK ET AL. 1973, STEINNOCHER 1997). HARALICK ET AL. (1973) are mentioning 14 of these textural features, some of which are as well implemented in eCognition™ as classification features.

[17] The *GLCM - Angular Second Moment* (ASM) corresponds to the sum of squares of the occupied elements of the GLCM and is therefore a measure of homogeneity. It effectively measures the number of transitions from one grey level to another and is high for few transitions. Thus, low values indicate heterogeneity (STEINNOCHER 1997, MATHER 2004).

[18] The *GLCM – Entropy* (ENT) measures disorder of the image (ZHANG ET AL. 2003).

[19] The Haralick feature *GLCM – Contrast* (CON) gives non-linearly increasing weight to transitions from low to high grey scale values. The weight is the square of the difference in grey level. Its value is a function of the number of high/low or low/high transitions in grey level. CON measures local spatial frequency (MATHER 2004, ZHANG ET AL. 2003).

it is the user’s decision which classes are considered suitable within the respective levels of the classification.



Class Hierarchy

- Level 1
  - background_l1
  - impervious_l1
  - shadow _l1
  - street_l1
  - vegetation_l1
  - very_dense_urban_l1
- Level 2
- Level 3
- Level 4
  - background_l4
  - impervious_l4
  - street_l4
  - vegetation_l4
  - very_dense_urban_l4
- Level 5
  - background_l5
  - impervious_l5
  - street_l5
  - very_dense_urban_l5
- Level 6
  - background_l6
  - impervious_l6
  - street_l6
  - very_dense_urban_l6
- Level 7
  - background_l7
  - street_l7
  - very_dense_urban_l7
- Level 8
  - background_l8
  - street_l8

Class Description

Name: vegetation_l4

Parent class for display: vegetation_l4

Modifiers: ☐ Abstract ☐ Inactive

- Contained
  - and (min)
    - **Mean qb_south_s3_subset1_merge1_ndvi >= 0.07**
- Inherited
  - and (min) (Level 4)
    - **Level = 4**

Class Description

Name: very_dense_urban_l7

Parent class for display: very_dense_urban_l7

Modifiers: ☐ Abstract ☐ Inactive

- Contained
  - and (min)
    - **GLCM Ang. 2nd moment (all dir.), qb_south_s3_merge1_s**
    - **GLCM Entropy (all dir.), qb_south_s3_merge1_subset1.im**
- Inherited
  - and (min) (Level 7)
    - **Level = 7**

Figure 6-10: Class hierarchy of the QuickBird training area of test site South s3 (Delhi, India) and descriptions of the classes “very dense urban” (level 7) and “vegetation” level 5. The development of the class hierarchy is comparably simple, as the differentiation is merely made between different land cover classes only and not simultaneously between land use classes.

Table 6-2: Criteria and corresponding threshold values used in the rule-based classification in eCognition™ — identification of very dense urban areas (informal settlements) within the training area of test site South s3.

Land cover class	Level	Type of criteria	Criteria**	Threshold**
Streets	8	Spectral*	Mean (street layer) Ratio (street layer) Relative border to brighter neighbors (street layer)	<=124 <= 0.01 >= 0.55
Very dense urban	7	Texture	GLCM - Angular Second Moment (all dir.) (1) GLCM - Entropy (all dir.) (1)	<= 0.00079 753.335
Impervious	6	Texture	GLCM - Contrast (all dir.) (NDVI)	>= 422.465
Vegetation	4	Spectral*	Mean (NDVI)	>= 0.07
Shadow	1	Spectral*	Mean difference to neighbors (abs) (NDVI) Mean (3)	>= 0.0327 <= 124

*Layer values
**All criteria (features) and corresponding thresholds were determined using the SEaTH methodology.

With the purpose to classify informal settlements, medium scale objects (level 8) were classified first. In this level it is distinguished merely between the classes "streets" and "background". Sequentially in level 7 (sub-objects of level 8) the class "very dense urban" is extracted and taken to the next smaller level. This hierarchical approach is used step by step to those levels in which the appropriate classes can be classified well ("impervious" — level 6, "vegetation" — level 4). This way, all land cover classes are classified gradually and each class is bequeathed to the smaller levels within the class hierarchy. The fine segments of the lowest level (1) are classified to characterize small scale urban structures of shadows. Finally, all extracted classes are merged to one land cover classification in the smallest object level (1). The remaining levels (2-3, 5, and 9-12) are not required further in this application. The intermediate levels (2-3 and 5) were solely important for the inheritance of the land cover classes. As they will be used in further analysis for the classification of more settlement types (dense urban, medium dense urban etc.) they have all been retained unchanged. Figure 6-11 represents the complete workflow of the applied classification.

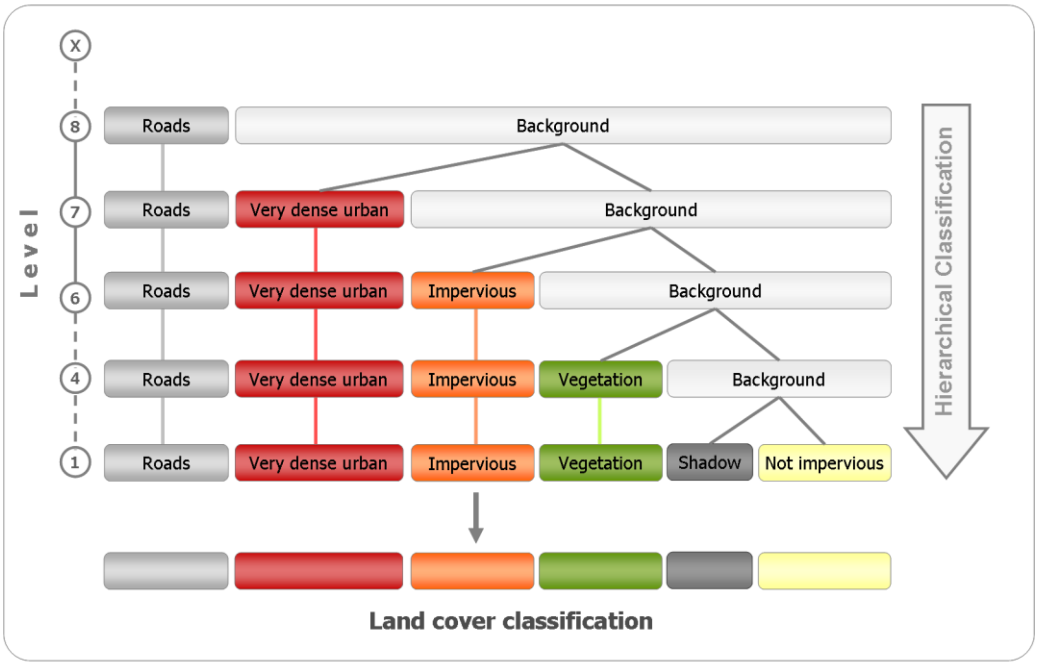


Figure 6-11: Modular framework for object-oriented urban land cover classification — identification of informal settlements (very dense urban areas) using a top-down approach.

One of the aims during the development of the classification approach is a robust spatial transferability. Within this study, particularly the identification of informal settlements within the urban area of Delhi is of major interest. The conceptual framework together with its classification approach was developed based on a training area within the test site South s3 (cf. chapter 4.2). A first test of the transferability of the classification method is carried out by application on the complete test site South s3. To prove the transferability of this concept further, a second test is carried out on a completely different "transfer site" (test site South s2) within the urban area of Delhi. The criteria set up for the development of the respective rule bases and their corresponding thresholds are provided in Appendix A.8. The results of the transfers are presented in chapter 7.2.1 and 7.2.2.

Not only the informal settlements within Delhi but also the other, on-site self defined and during the field campaign mapped settlement types (cf. chapter 5.3) shall be identified. For this purpose the developed method was adapted accordingly. The features and thresholds crucial for the separation of the classes were as well determined by SEaTH and subsequently implemented in eCognition^{TM}. Firstly the research was focused on the identification of "sparse urban" settlement areas. As this settlement type can, like informal settlements, be considered as a type with "extreme features", i.e. the settlement type can due to its characteristics clearly be separated from the surrounding settlement areas, the methodology could comparably easily be transferred. Sparse urban areas are characterized, in contrast to informal settlements, by a very low building density, i.e. the fraction of impervious area is very low. At the same time vegetation covers a large fraction of the total area, which are mainly gardens surrounding private homes. The size of the residential buildings is in the mid-range. Consequently, completely different textural and spectral properties are distinctive, so that the classification features of this settlement type need to be newly determined by SEaTH. The considered features and their respective thresholds are listed in the Appendix in Table A.8.2. As another test site South s2 needed to be chosen for this classification, not exactly the identical levels could be used for the identification of the respective classes. The choice of the classification levels has hence slightly been modified.

The transfer of the methodology on the remaining settlement types "dense urban" and "medium dense urban" figured out to be not trivial though. Difficulties occurred at the determination of significant features for optimal class separation and the corresponding thresholds, as the attributes of the selected sets of training data in parts hardly differed. The procedure was repeated several times, in order to except that the selection of the set of the training data for the determination of the features is the root cause of the problem. Looking at the sub-objects, one can easily recognize why a clear separation of the settlement structures is difficult — even by a visual assessment the differences can hardly be identified (cf. Figure 6-12 and Figure 6-13).

However, in order to enhance the quality of the classification results, an approach was adopted, which was already used by other authors for the evaluation of VHR remote sensing data within urban areas — to combine both object-oriented and pixel-based algorithms and thus to take advantages of their respective pros and cons (cf. chapter 3.2.2). Considering this, an ancillary layer as input data for the development of the rule base was added. This layer is resulting of a supervised pixel-based classification, which was performed simultaneously to the object-oriented classification (cf. Appendix A.9). As the data base for this classification is completely different here, the class hierarchy developed for the identification of the previous settlement types could not be transferred directly. Hence, not only the thresholds needed to be determined newly with the SEaTH methodology, but as well the criteria needed to be re-evaluated and implemented into the rule base in eCognition^{TM}. Again the textural features were the decisive parameters for the classification of the settlement structures. In addition to that, the selection of the levels of the class hierarchy, in which the corresponding classes were identified, was adjusted to the new approach (cf. Appendix, Table A.8.3).

Figure 6-12: Merged QuickBird training area in 4/3/2 composite (top). The sub-objects (segmentation level 7) show that a clear separation of the settlement types "dense urban" (red object) and "medium dense urban" (green object) is difficult — even by a visual assessment the differences can hardly be identified (bottom).

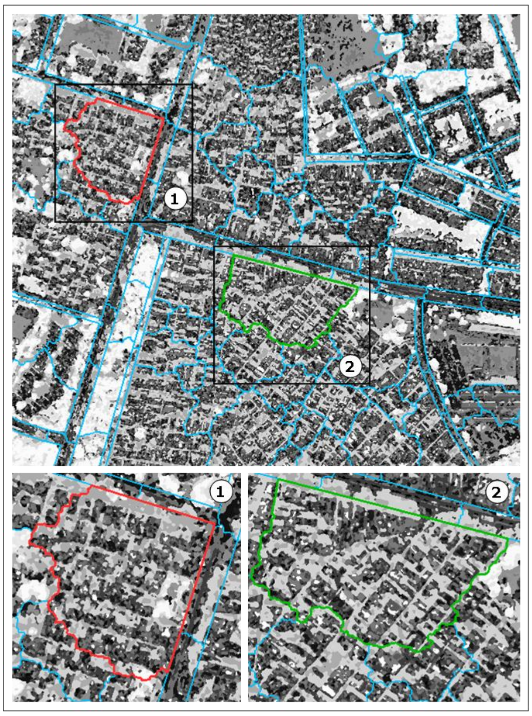


Figure 6-13: Result of pixel-based image classification displayed in grey scale values based on merged QuickBird training area (top). The sub-objects (segmentation level 8) show that a clear separation of the settlement types "dense urban" (green object) and "medium dense urban" (red object) is difficult — even by a visual assessment the differences can hardly be identified (bottom).

Based on the image analysis conducted using the eCognition^{TM} software the following strenghts of the object-oriented technique (in general and using the eCogntion software in particular) can be summarized:

- The good suitability as well for multi-resolution segmentation as for the image analysis to the spatial and radiometric information of the real world objects,
- The availability of an immense amount of criteria to characterize and define the desired classes,
- The possibility to optimize the methodology by implementing ancillary thematic information, such as a GIS layer or NDVI image,

- The potential, in principle[20], to instantly transfer the developed classification scheme to another test site or image with similar land cover (protocol function), as well as
- The classification results can be exported in form of thematic vector layers, which enables close connection to GIS and for instance further integrative data analyses.

Nevertheless, disadvantages of the applied object-oriented approach and the software eCognition^{TM} with respect to a successful and operational application have to be mentioned. In general an image analysis using this tool is involved with a significant expenditure of human labor, requires significantly higher skills, is more complex and time consuming than the conventional methods (ESCH ET AL. 2003). In detail the following facts are crucial:

- The identification of appropriate parameters out of the immense range available and the determination of respective thresholds towards the segmentation and classification usually mainly bases on estimations or experiences of the analyst. Hence, the development and performance of the object-based image analysis can easily become very complex. (With regard to this research this fact could be kept in check using the SEaTH algorithm.)
- The great variety of usable features and sub-procedures leads on the one hand to a high variability of the approach but aggravates on the other hand the comprehensibility of the methods and structural dependencies for new users.
- The effort and time exposure can hardly be estimated in advance.
- Working with various levels and/or large images (in respect of spatial resolution as well as spatial dimension) can increase the processing time exponentially (ESCH ET AL. 2003, KAMPOURAKI ET AL. 2006).

eCognition^{TM}, in fact, cannot interpret an image as intelligently as a manual interpreter would, but the results turned out satisfactory in that manner that it is possible to pass on substantial information (in respect of content) or to carry out continuative analyses.

The results of the object-oriented classification are presented in chapter 7.2.

6.2 Integrative Use of Remote Sensing Derived Information and Socio-economic Data

According to the explanations in chapter 3.3 one of the limitations within the exclusive use of remotely sensed data is based in the fact that no socio-economic information can be

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[20] once the user finds the appropriate parameters and thresholds for a satisfactory segmentation and classification

provided directly and therefore also no direct characterization of the living conditions within a certain settlement area is possible. It is for instance impossible to sense the amount of residents per housing unit without the application of ancillary in-situ information. At the same time, in the majority of cases, there are almost no or only incomplete datasets available in less developed countries. Particularly mega cities like Delhi are data poor environments. Temporal resolution, coverage and quality of administrative and socio-economic data are insufficient and the knowledge about the living conditions of the residents is correspondingly very limited, incomplete and not up to date. Due to logistical reasons, as well as the high time and cost intensity of the acquisition of in-situ data this circumstance will not approve within the near future. Therefore, within the following chapter a methodology is developed to compensate the lack of in-situ collected socio-economic data by means of remote sensing imagery as well as with the integration of questionnaire data in order to allow an indirect assessment of the living conditions of Delhi's inhabitants. The combined application of remotely sensed imagery and socio-economic data for mapping, capturing and characterizing the socio-economic structures and dynamics within the mega city of Delhi is the major task within this research.

In order to examine whether high-resolution remote sensing data is suitable to provide indicators to identify socio-economic structures and dynamics, the classification results [1] were embedded in a GIS analysis concept [2]. This concept is used to determine different socio-economic attributes, such as the population amount or the population density, and to evaluate the water demand within a certain settlement area. The framework to this approach is presented in Figure 6-14.

According to COWEN & JENSEN (1998) the derivation of socio-economic attributes using remotely sensed data usually requires the fulfilling of several preconditions. In order to estimate population attributes, which is one of the tasks within this study, it is necessary to (1) have access to imagery with sufficient spatial resolution to allow the identification of individual structures and to determine whether buildings are residential or not. In addition, (2) some estimates of the average number of persons per dwelling unit must be available and (3) it must be assumed that all dwelling units are occupied, and only one family lives in each unit. Otherwise, the analyst needs more detailed information on the living conditions of the residents (e.g., number of families per house, housing units per building, and stories). Since VHR QuickBird data is used within this study, the requirement for imagery with sufficient spatial resolution is conformed. The second precondition is fulfilled as well, as, based on the questionnaire data (cf. chapter 5.2), adequate information on the average family size is available. For the investigation of informal settlements or other one-family dwelling settlements, such as the upper middle class settlement *Greater Kailash II* or the upper lower/lower middle class settlement *Tughlakabad Extension*, also the third requirement is conformed. For the analysis of the remaining settlement types examined in this research (e.g., *Kalkaji DDA Flats*) ancillary information, namely the average number of stories, is applied to estimate the number of inhabitants.

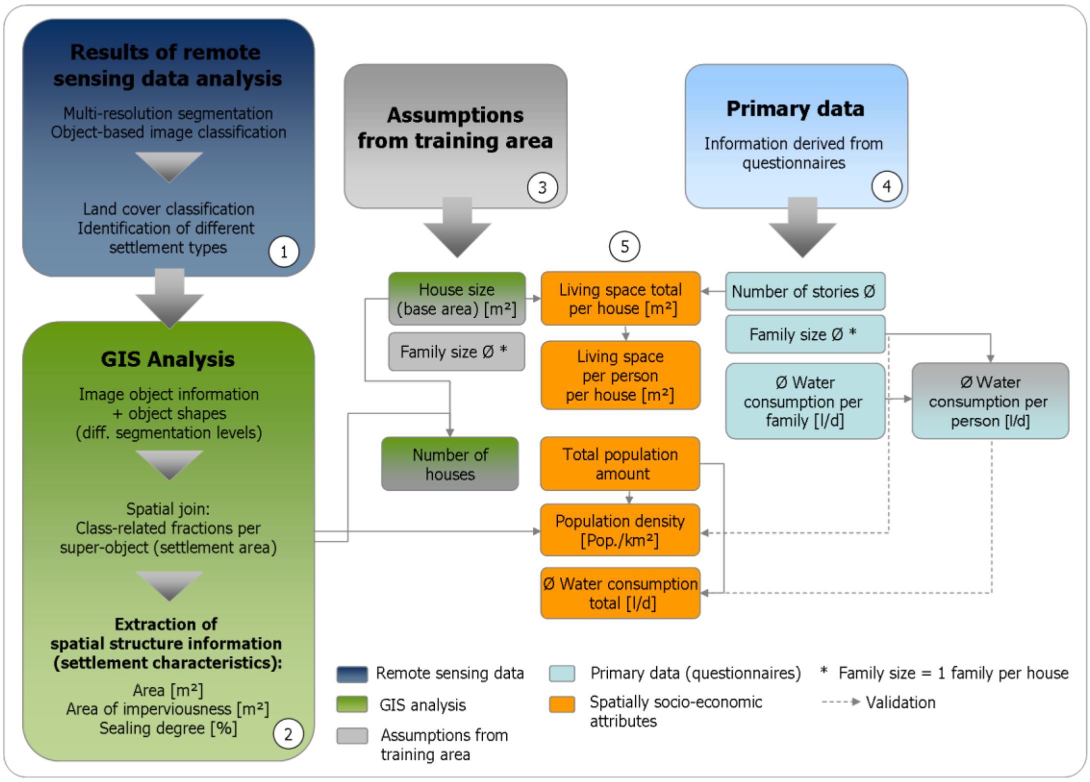

Figure 6-14: Detailed framework of the work steps implemented in the integrative data analysis. Further explanations are included in the text.

Within this study, the settlement characteristics (e.g., area, house size, and number of houses) are estimated from the classified QuickBird data and used to derive spatial information about the population distribution [2+3]. In order to obtain these characteristics the following approach was implemented:

4. Export of the settlement image objects after classification, which are characterized by shape features (e.g., object size) only or additionally by class information (i.e. an object is assigned to a certain land cover class),

5. Determination of the impervious fraction of a certain object (settlement) using the results of object-oriented image classification in combination with GIS queries,

6. Determination of the mean building size (A_H) within the settlement area by means of mapping randomly sampled buildings within a GIS environment and their automatically statistical calculation using arithmetic mean (cf. Appendix, Map A.10),

7. Evaluation of the total number of houses (N) within the settlement by dividing the impervious area (A_I) by the mean building size (A_H).

This approach is tested in two ways: (1) the settlement is represented by one image object only (e.g., level x), and (2) two or more image objects together build up one settlement (e.g., level x-1). The results of this examination show that both methods enable the estimation of various settlement characteristics in the same way. Therefore, it is not necessary to extract the settlement to be examined with one fitting object — the settlement can consist of more segments. In turn, this makes the methodology more independent of the results of the segmentation process.

In addition, the integrative approach makes use of the primary database [4] (georeferenced questionnaires, cf. chapter 5.2). These are used to characterize a given settlement type in terms of specific population and water related variables (e.g., family size, mean water consumption per family member and per capita in a certain settlement). The parameter "family size" was calculated using the arithmetic mean:

$$F = \bar{x}_{arithm} = \frac{1}{n}\sum_{i=1}^{n} x_i = \frac{x_1 + x_2 + ...x_n}{n}$$

Equation 6-7

F = average family size per settlement,
n = number of interviewed households,
x = number of family members per household.

In contrast to the given information on the family size per household, the interview information on the water consumption was often doubtful (cf. chapter 5.2.3). Hence, extreme outliers, which could definitely be considered as unrealistic data, were eliminated accordingly. Afterwards the "mean water consumption per capita" within a settlement was determined using the arithmetic mean as well:

$$W_C = \frac{1}{n}\sum_{i=1}^{n} w_i = \frac{w_1 + w_2 + ...w_n}{n}$$

Equation 6-8

W_C = mean water consumption per capita [l/d] within a settlement,
w = mean water consumption per family member per interviewed household
n = number of interviewed households.

By combining the remote sensing derived data with the questionnaire information, it is possible to characterize a given settlement type (e.g., informal settlement) in terms of specific population and water related parameters, such as "total population", "population density" and "total water consumption" [5]. For instance, the total population amount of a certain settlement was established by the following approach:

$$P = N \cdot F$$

Equation 6-9

P = total population of the settlement,

N = total number of houses within the settlement extracted from satellite image,
F = average number of persons per household (family size) extracted from questionnaire data (family size = 1 family per house; calculated using arithmetic mean).

In the following, the population density of a settlement area was calculated as:

$$D = P / A_S$$

Equation 6-10

D = population density [Pop./km²] of the settlement,
P = total population of the settlement,
A_S = settlement area (estimated from multi-resolution segmentation) [km²].

The total water consumption of all inhabitants living in a certain settlement is calculated using the correlation:

$$W_T = W_P \cdot P$$

Equation 6-11

W_T = total water consumption [l/d] of the settlement,

W_C = mean water consumption per capita [l/d] within the settlement (extracted from questionnaire data, cf. formula 6-8),

P = total population of the settlement.

In order to compare the remote sensing derived data (assumptions) with the questionnaire data, a realistic amount for "water consumption per capita" [l/d] was estimated. In this case for informal settlements in Delhi an empirical value of 25 [l/d] was determined.

It is important to note that the remote sensing and primary data has been strictly divided into two parts: one part for the methodology development and the other for the validation of the approach. To transfer the approach to unknown areas, where no primary data has been collected, assumptions have to be made for certain variables (e.g., family size, water consumption), which might result in uncertainties in the estimated variables.

The results of the integrative analysis are all presented in chapter 8.

Chapter 7

Identification of Urban Structures Using VHR Remote Sensing Data

In this section, the results of the object-based image data analysis are presented. At first, the deliverables of the segmentation process are presented (cf. chapter 7.1). In chapter 7.2 then, the deliverables of the object-oriented classification approach are demonstrated. This includes the identification of informal settlements and other settlement types within the urban area of Delhi (cf. chapter 7.2.1 and 7.2.2). The quality of the land cover classification is of decisive importance for the following investigation of the urban environment of Delhi. In order to estimate the achieved accuracy of this process, hence the mapping results were evaluated both in qualitative and in a quantitative way (cf. chapter 7.2.3). The section is completed with a summary and a critical survey of the classification results (cf. chapter 7.2.4).

7.1 Deliverables of the Segmentation Process

In the next two sub-chapters initially the outcome of the segmentation process is shown (cf. chapter 7.1.1). Subsequently, since the image objects extracted here are crucial for the image classification following, the results and the segmentation method itself are appraised within this chapter as well (cf. chapter 7.1.2).

7.1.1 Results of the Multi-Resolution Image Segmentation

As explained in detail in chapter 6.1.1 in this research a bottom-up approach with very fine segmentation on the base level (level 1) and coarse segmentation on the top level (level 12) was applied in order to facilitate the retrieval of meaningful objects for the classification of different land cover classes and different settlement types. This means that altogether 12 levels were calculated where level 1 represents the smallest objects and level 12 represents the biggest objects of the segmentation process (cf. Table 6-1 in chapter 6.1.1). Using this approach the primary aim was to prove the assumption that it is the textural information of the image data, which is in particular essential for the detection of different settlement types. This is especially true for the detection of informal settlements.

As can be observed in Figure 7-1 and Figure 7-2 multi-resolution segmentation was successfully applied to the acquired QuickBird image data of the city of Delhi. Figure 7-1 shows a sequence of segmentation levels which was produced from the analysis of the chosen training area of this study whereas the segment sizes are optimized in terms of best fitting representation of the real world structures. To take advantage of the textural information, objects on the top level (here level 9-12) outline more or less different settlement areas, large parts of settlement areas and other objects of comparable size (e.g., industrial areas, large unimproved areas, or large green corridors). Clearly visible is for example in level 9 of the simplified illustration in Figure 7-2 that the settlement area with the highest building density in the middle-northern part of the training area is being delimited as a segment. This area comprises a part of the informal settlement *Bhomiheen Camp* (cf. chapter 7.2.1 and Figure 7-5). Intermediary segmentation levels (here level 5-8) are necessary for the identification of medium scale objects (smaller settlement areas, large and medium sized buildings, open and green spaces etc.). Segments on the bottom level (here level 1-4) outline the smallest image contents. The base level (1) and the three next higher level hold for instance image objects which coincide with the smallest residential buildings, as well as with small road segments, small vegetation areas, and small areas of shadow. Hence, the requirement that the parameters should be selected within the first segmentation step in a way that the smallest segments required for the subsequent analysis are generated (cf. chapter 6.1.1), is met.

The segmentation parameters were chosen based on the accuracy of the segments delineating the boundaries of the small (single residential buildings) and large objects (e.g., green and open spaces as well as settlements itself) visible in the image.

The resulting segmentation needed to be reproducible and universal to permit application to the largest variety of data possible. Hence, after testing the multi-resolution image segmentation on the selected training area, the developed segmentation approach was firstly transferred to the whole test site South s3 and secondly to the transfer site South s2 correspondingly. As during the segmentation of the training area fixed parameter settings were applied here as well and the scale parameter was changed systematically like before.

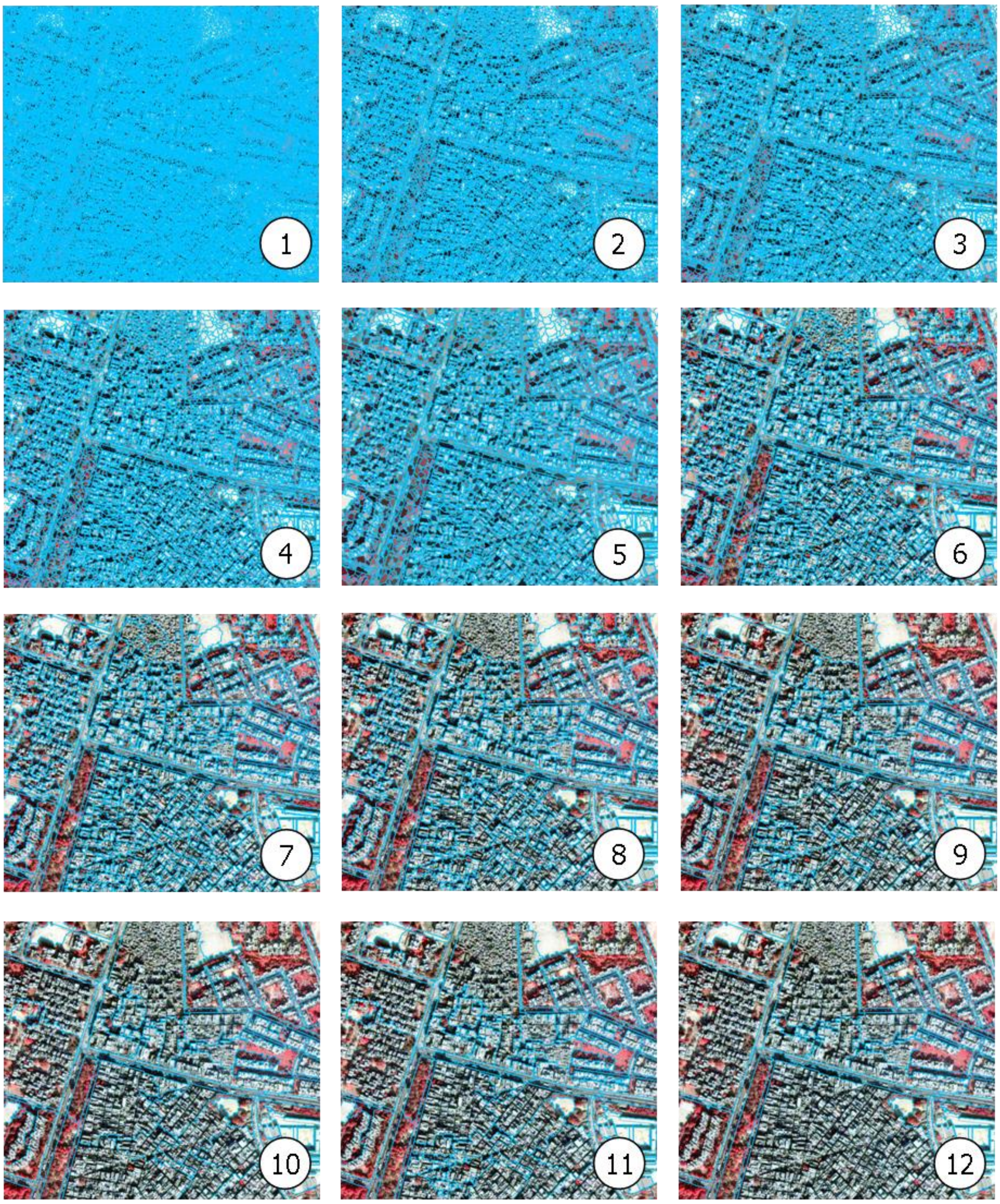

Figure 7-1: Results of multi-resolution image segmentation based on the training area. The scale parameter was changed systematically, while the residual homogeneity parameters and the layer weights remained constant (shape [0.5], color [0.5], smoothness [0.3], and compactness [0.7]). The images are numbered according to their segmentation level: 1 — scale 5, 2 — scale 10, …, 12 — scale 200.

Figure 7-2: Simplified illustration of the results of multi-resolution image segmentation with varying scale parameter of training area of test site South s3: 1 – scale 5 (level1), 2 – scale 25 (level 5), 3 – scale 125 (level 9), 4 – scale 200 (level 12). The blue highlighted segment in level 9 demarcates the area with the highest building density, which is a part of the informal settlement *Bhomiheen Camp*.

The transfer results shall here exemplarily be illustrated on the basis of test site South s2. The segmentation results of test site South s3 are not presented in detail here. The detailed results can be found in the appendix (cf. A.11). Figure 7-3 illustrates the results of the multi-resolution image segmentation based on the transfer site South s2.

The developed segmentation procedure and therefore the fixed parameter settings and the defined scale parameters were subsequently applied to the transfer site South s3. Consequentely, the area under investigation was segmented on 12 levels as well. It is visible in the segmentation results of the test site, that very small items such as the smallest residential buildings were demarcated at the fine-scale level (level 1-5). Larger buildings and smaller settlement areas for instance were segmented at the medium-scale level (level 6-8) whilst at the coarse scale-level (level 9-12) large entities such as whole settlement areas or large unimproved areas were demarcated.

The transfer of the defined segmentation process to a completely different test site South s2 was, thus, accomplished successfully, too. As shown in Figure 7-4 in detail this way, for instance, again in level 9 the settlement area with the highest building density – the informal settlements *Banjara* and *Harijan Camp* –, located at the main road, was clearly visible delimited as one image object (cf. chapter 7.2.1 and Figure 7-8).

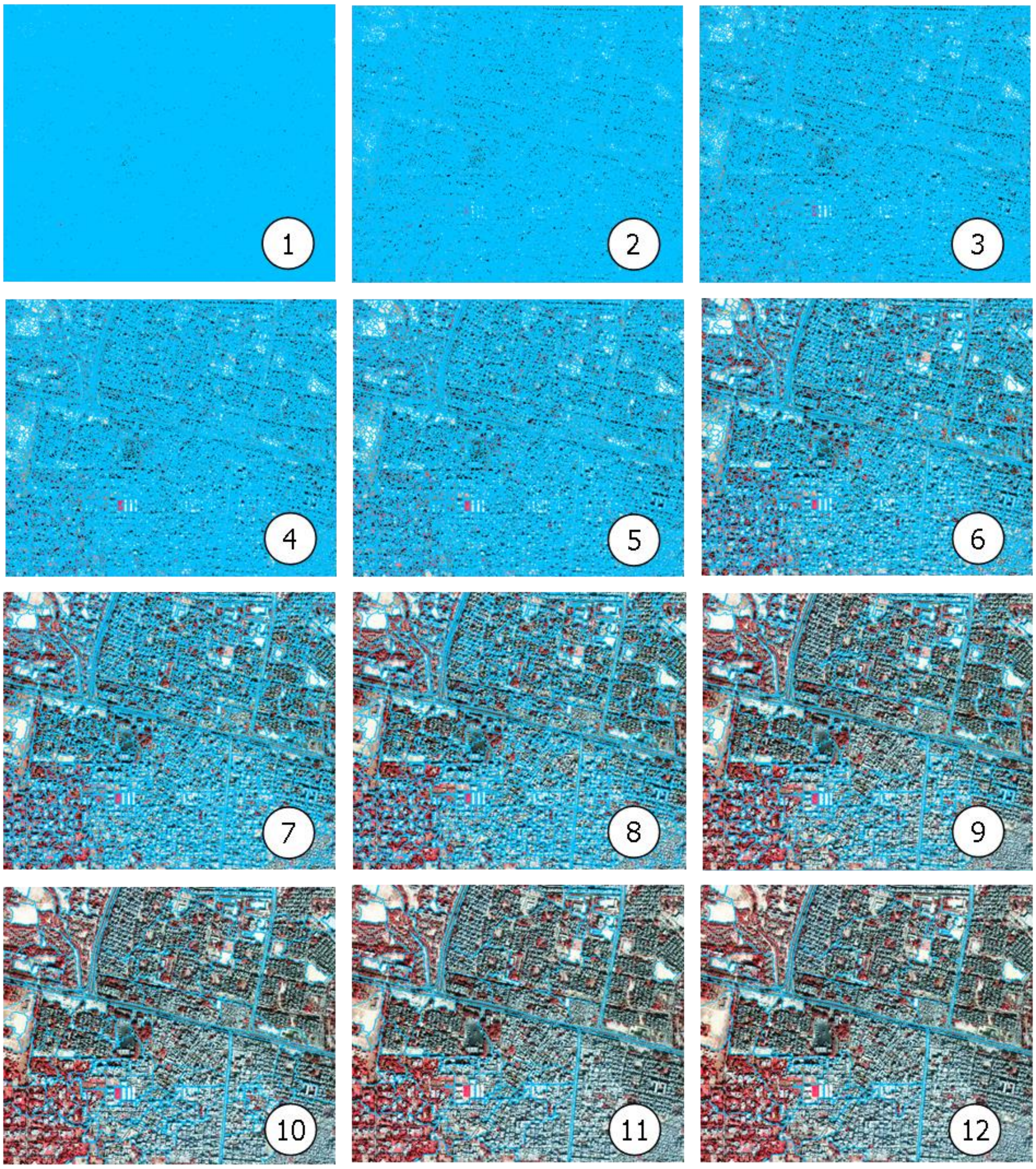

Figure 7-3: Results of multi-resolution image segmentation based on the transfer site South s2. The scale parameter was changed systematically, while the residual homogeneity parameters and the layer weights remained constant (shape [0.5], color [0.5], smoothness [0.3], and compactness [0.7]). The images are numbered according to their segmentation level: 1 — scale 5, 2 — scale 10, … , 12 — scale 200.

Figure 7-4: Result of multi-resolution image segmentation based on the transfer site South s2: segmentation level 9 with scale parameter 125. The yellow highlighted object delimits clearly the area with the highest building density within this test site. The delineation is consistent with the settlement boundaries of the merging informal settlement areas of *Banjara* and *Harijan Camp.*

Since the classification process is based on the segment properties generated, a substandard segmentation quality has an adverse effect on the classification quality. Hence, in the following chapter 7.1.2 the segmentation method itself and the results are appraised.

7.1.2 Appraisal of the Segmentation Results and Method

Since the quality of image classification is directly affected by the segmentation quality, the segmentation process and the image objects produced are of high importance for the subsequent analysis (cf. chapter 6.1.2 and 7.2). "As a rough rule of thumb it can be stated that, the better the generated segments are capable to represent the imaged objects in the image data, the better the quality of the segmentation process and consequently the classification results are" (HOFMANN ET AL. 2008). Thus, the segmentation is the Achilles heel of the object-oriented remote sensing information retrieval process.

According to this, it is important to answer the question 'How good is the applied segmentation algorithm?'. Methods for the evaluation of segmentation results are discussed for example by NEUBERT ET AL. (2006), ZHANG ET AL. (2004), MEZARIS ET AL. (2003), LETOURNEL ET AL. 2002 or LEVINE & NAZIF (1985). However, it has been established that at present the most reliable evaluation method is still "a visual interpretation that has to consider the exact geometrical position of the segment borders as well as the membership of one and only one object class to a single region" (SCHIEWE 2002). Logically this means that the homogeneity features and parameters and the generalization level are subjectively determined. Within this research too, solely a visual interpretation and assessment of the generated image objects was applied. A quantitative evaluation of the segmentation results was resigned due to the disproportionately high efforts necessary. The image segmentation performed in the context of an object-oriented classification approach provided for both the training area and the complete test sites South s2 and s3 meaningful spatial units. Moreover, the image segmentation leads, compared to pixel-based image analysis, to a better outlining of real world structures and objects, for example single residential buildings or complete urban settlement areas. This means that the resulting segments come closer to the spatial and therefore spectral and textural characteristics of the individual and complex urban structures in a mega city environment. Furthermore diverse shape- or context-related attributes were provided. The possibility to produce a discretionary number of segmentation levels was achieved while the segment sizes were optimized in order to best represent the real world structures. All in all, it can be stated, that regarding the complex and heterogeneous structures of the different settlement types within Delhi, eCognition´s multi-resolution segmentation is well suited to generate meaningful image objects.

Nevertheless, already during the sensitivity study (cf. chapter 6.1.1) it turned out that the process of the applied software eCognition^{TM} and the included image segmentation implicates significant difficulties. With respect to an operational application, on the one hand, the determination of the optimum number of levels and the corresponding segmentation parameters was very complex and therefore very time-consuming.

This disadvantage was encountered actively though within this study by a fixation of the parameter settings based on the sensitivity study, in contrast to a case by case determination for each new test site. Doing so, it was accepted that the generated image objects do not always perfectly match the real world structures. Aiming to develop an operational, i.e. global approach, one has to accept to do without such a refinement.

In any case, the prevalent studies have proven that the different test sites could be segmented with a sufficient quality and that the generated segments together with their properties form a very good basis for the subsequent classification process. The segmentation process using the eCognition^{TM} software is in itself a very time-consuming procedure though, which requires an extensive computation capacity. Therefore it is generally recommendable to initially apply test runs to smaller image subsets which are representative for the whole scene. Since eCognition^{TM} with the release of version 3.0 uses a segmentation algorithm which allows for the generation of image size independent results, this line of action is not critical in terms of reproducibility of the segments and therefore not either for the following classification.

7.2 Deliverables of the Object-oriented Classification Approach

Based on the segmentation derived building blocks and on the developed class hierarchy a land cover classification of selected sites within the urban area of Delhi was performed. Within this study, it is postulated that the structure of a settlement is mirroring the living conditions of its inhabitants. In order to prove this thesis, during the classification process the identification of different settlement types — regarding especially their building size and density — was put into the focus.

In this process, priority was given to the identification of informal structures, i.e. informal settlements. These informal settlements are the most visible expression of urban poverty in the mega city of Delhi. Their physical entity is a result of the inadequate social circumstances the inhabitants are living in. In order to carry out the urban planning and development tasks necessary to improve the living conditions for the poorest residents of the mega city, the identification of such "hot spots" of urban challenges is a basic precondition.

Beyond that, the on-site defined and during the field campaign mapped settlement types (cf. Figure 5-12 and Figure 5-13 in chapter 5.3) should be identified using the developed classification methodology. The diverse living conditions of these inhabitants should be, according to the working thesis, directly visible in these settlement structures as well.

Comparable to the execution of the segmentation process, at first, the classification methodology was developed and tested based on the chosen training area within test site South s3. Then the approach was applied to the whole test site South s3. In order to explore the transferability the developed classification methodology was carried out afterwards on a completely different test area within the mega city of Delhi, namely South s2.

The following subchapters provide the results of the object-oriented classification approach.

7.2.1 Identification of Informal Settlements within the Urban Environment of Delhi

The final outcome of the object-oriented classification approach is presented in the urban land cover classification in Figure 7-5. All in all, six land cover classes — impervious, not impervious, vegetation, roads, shadow and very dense urban — could be identified. Their spatial distribution, which represents a relatively up to date and spatially comprehensive piece of information, therefore gives an answer on the "what is where" within the complex and heterogeneous urban morphology of the examined district within Delhi. Of particular importance hereby is, that the area with the smallest buildings and highest building density — represented by the class "very dense urban" — can be clearly separated from the remaining impervious areas. This area is a part of an informal settlement (*Jhuggi Jhompri* cluster) which is called *Bhomiheen Camp*. The *Bhomiheen Camp* represents an illegal residential area tolerated by the Indian government, which is characterized in general by an inadequate supply situation and in particular by a considerably insufficient water supply and waste water disposal system (cf. chapter 8.1). The mostly one or two storied houses here are constructed in a very simple, improvised style (cf. Figure 7-6).

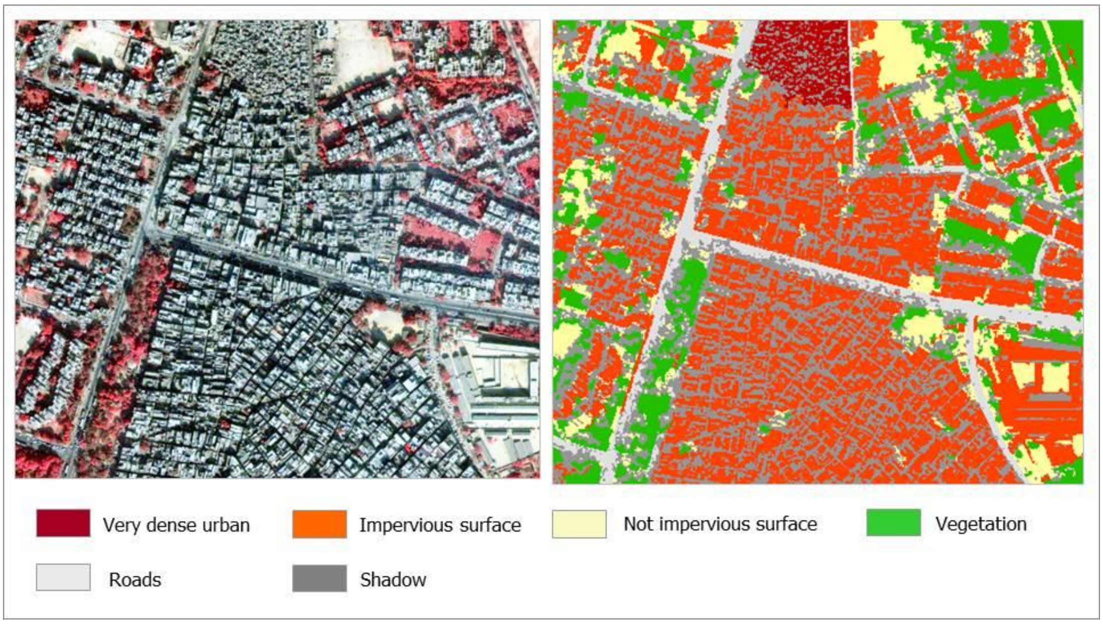

Figure 7-5: Training area of the fused QuickBird test site South s3 (4, 3, 2) versus the result of object-oriented image classification: In the classified image subset "very dense urban" areas could be successfully identified. The mapped very dense area is part of the informal settlement *Bhomiheen Camp*. Further explanations are included in the text (enlarged Map cf. Appendix, A.12.1).

The remaining impervious areas comprise different kinds of settlements. Areas of the middle and the upper lower class are represented here next to the informal settlement. These settlement types are as well characterized by various structures, which implicate e.g., different building sizes or building densities. Also the relations between the buildings (sub-objects) within the various settlements (super-objects) are varying and are different amongst each other. In order to make these facts usable and to prove whether this approach is generally applicable, it is an objective of this study to differentiate these settlement types, too. The results of the respective investigations are summarized in the following chapter 7.2.2.

Figure 7-6: Impression of the informal settlement *Bhomiheen Camp* located within the training area of test site South s3 *(Photographs: S. Smollich, October 2005)*.

The detail view in Map A.12.1 (cf. Appendix) reveals the potential of this method to partially capture single houses with high precision, and hence to map the physical characteristics of the urban landscape true-to-detail. But, it becomes also evident that an identification of single buildings within the informal settlement is very difficult. The reason for this is on the one hand the very high building density of this settlement type. The houses are mostly attached to each other, which means that no or hardly any gaps are visible. Hence shadows, which would make the delineation/classification easier, are not or hardly existent. On the other hand, in a large part the houses have been constructed from the same building material. Therefore no spectral discrepancies exist between different buildings, which would enable a differentiation by means of satellite data. Which makes it even more difficult is the fact that surface material of the little walkways between the houses — the mapping of which would facilitate the differatiation — is spectrally speaking very similar or even equal to the building material of the houses. A fully automatic extraction of residential buildings in informal settlements in Delhi using only remote sensing is therefore not offhand possible with the applied method and this defines at the same time the boarderlines of the approach and the used data.

The classification result in Figure 7-5 shows furthermore that the residual land cover classes — vegetation, not impervious surface, roads and shadow — can be identified successfully. The quality of the land cover classification is examined in more detail in chapter 7.2.3.

As mentioned before, the methodology developed for the training area was tested on its transferability and general validity. Therefore the whole test site South s3, characterized by similar settlement structures, was analyzed initially (cf. Figure 7-7). It is well visible that the identification of "very dense urban" areas is also possible within this site. The informal settlement *Bhomiheen Camp* could be extracted completely as well as the *Nehru* and

Navjeewan Camp, which are located adjacent in the North. The remaining classes also represent the reality correctly. The detail views in Figure 7-7 and the enlarged Map A.12.2 (cf. Appendix) enable a more precise visual interpretation of the classification accuracy and quality.

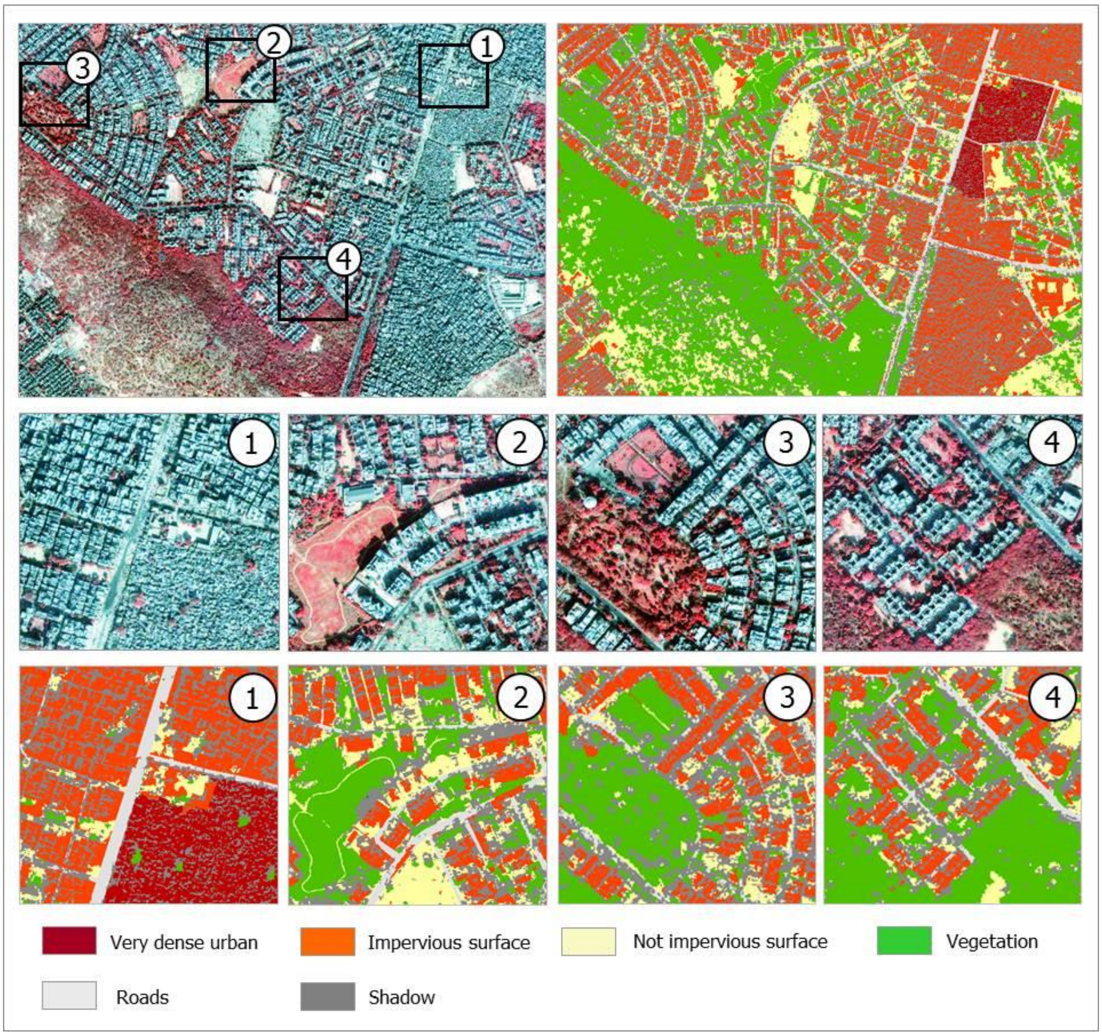

Figure 7-7: Fused QuickBird test site South s3 (4, 3, 2) versus the result of object-oriented image classification: Identification of "very dense urban" is possible. The informal settlements *Bhomiheen Camp* as well as *Nehru* and *Navjeewan Camp* could be extracted completely (enlarged Map cf. Appendix, A.12.2).

The transfer of the developed classification approach to a completely different test area South s2 was accomplished successfully, too (cf. Figure 7-8). The *Banjara* and *Harijan Camp*, located at the main road, were identified clearly as "very dense urban" area. As the informal settlements mentioned before, these camps represent illegal residential areas which are characterized by a lack of basic infrastructure services (cf. Figure 7-9). One additional district was identified as "very dense urban". This area (lower right corner) is in fact very dense, but it does not represent an informal settlement. Instead it is an urban village — a characteristic of Delhi —, namely *Deoli*, with mostly similar physical attributes (cf. Figure 7-10).

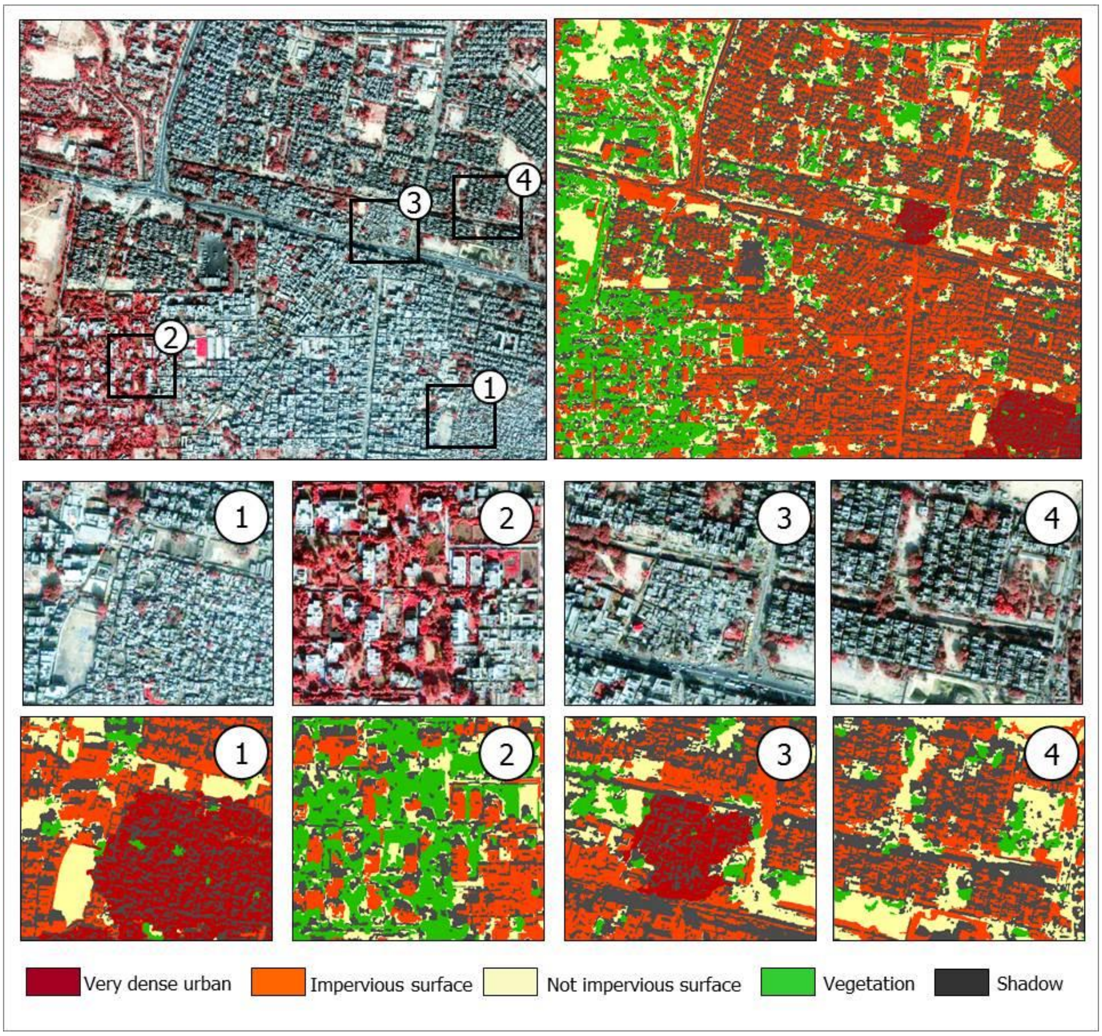

Figure 7-8: Fused QuickBird transfer site South s2 (4, 3, 2) versus the results of object-oriented image classification: Application of the developed classification approach to a completely different test area. The *Banjara* and *Harijan Camp* located at the main road — both informal settlements— were identified as "very dense urban" area (enlarged Map cf. Appendix, A.12.3).

In contrast to the JJ-colonies, urban villages are not assigned to informal settlements on the one side because of their judical status. On the other side, they are not assigned to this class because the quality of the living conditions of the inhabitants, despite being very poor and showing slum similar conditions due to their disadvategeous development, are still in average higher than they are in informal settlements. This example shows that there are still some limits of the application of VHR remote sensing data. Without additional socio-economic data or on-site information, a differentiation of settlement types with a physically very similar characteristic is not possible. All in all, the results still show that the areas with the supposedly worst living conditions and the poorest supply situation can be clearly identified (semi-) automatically.

Figure 7-9: Impression of the informal settlement *Banjara* and *Harijan Camp* located within test site South s2. These camps represent an illegal residential area which is characterized by a lack of basic infrastructure services *(Photographs: S. Smollich, October 2005 and R. Singh, March 2006)*.

Figure 7-10: Impression of the urban village *Deoli* located in the southeast of test site South s2. Due to their disadvantageous development urban villages in Delhi show a slum similar structure. But the quality of living conditions of the residents here is in average still higher than of those living in the JJ-colonies *(Photograph: S. Smollich, October 2005)*.

7.2.2 Identification of Further Settlement Types within Delhi

One important goal of the object-oriented classification approach is the transferability to different settlement types within the mega city of Delhi. Thus, using the developed classification methodology, the remaining on-site defined and during the field campaign mapped settlement types should be identified as well. Figure 7-11 presents a first transfer result of the object-oriented classification scheme. As expected, the approach could successfully be applied to the identification of the settlement type "sparse urban". This settlement type can, as well as "very dense urban" areas, be considered as a settlement with "extreme attributes", i.e. the settlement type could, due to its characteristic outward appearance, clearly be separated from the surrounding settlement areas or land cover classes, respectively.

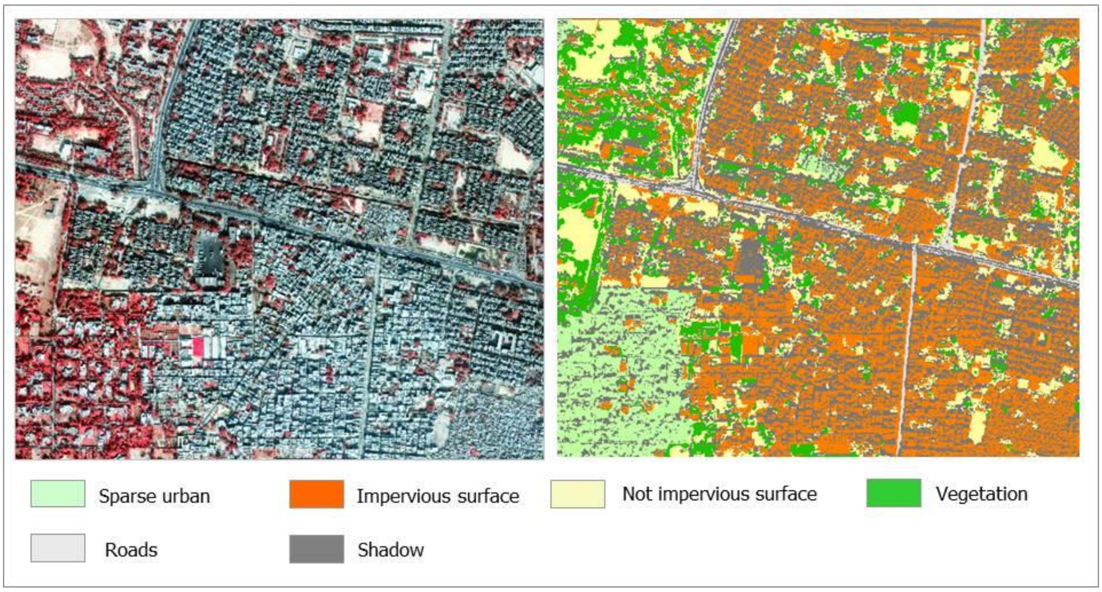

Figure 7-11: Identification of further settlement types within the fused QuickBird test site South s2 (4, 3, 2). Within the classified test site "sparse urban" areas could be identified successfully. The unauthorized colony *Sainik Farms*, located in the southwest of the test site, could be clearly separated from the surrounding areas. The residents of the sparse urban area belong to Delhi's upper class (enlarged Map cf. Appendix, A.12.4).

The sparse urban settlement located in the southwest of the test site is known as the unauthorized colony *Sainik Farms*. *Sainik Farms* is one of the so called *farm house* quarters of Delhi, the residents of which belong to the upper class of the city. Being former agricultural areas, these quarters are holding special rights regarding the utalization of water — e.g., deep water drillings are allowed in order to extract ground water (ZERAH 2000). This means that the inhabitants have a more than sufficient water supply, despite the settlements are not attached to the municipal water supply due to their informal status, and despite the fact that the southern districts are generally disadvantached due to the water works being mainly situated in the northern districts. At times, when the wells do not deliver enough water, the inhabitants cover their high demands, which is mainly driven by the watering of their private gardens (cf. Figure 7-12), by bying additional water out of tank trucks. According to TREVEDI ET AL. (2001) this inadequate withdrawal of ground water is enforcing the continuous drop of the ground water level of the whole mega city in general but in special of the southern districts. The per-capita consumption of 382 lpcd as mentioned by ZERAH (2000) confirms that particular sections of the population are consuming inadequately high amounts of water, while at the same time the major percentage of the population of southern Delhi is suffering of an insufficient water supply (cf. chapter 8.1).

Figure 7-12: Upper class colony *Sainik Farms*, located in the South of Delhi (*Photographs: S.Smollich, Oct. 2005).*

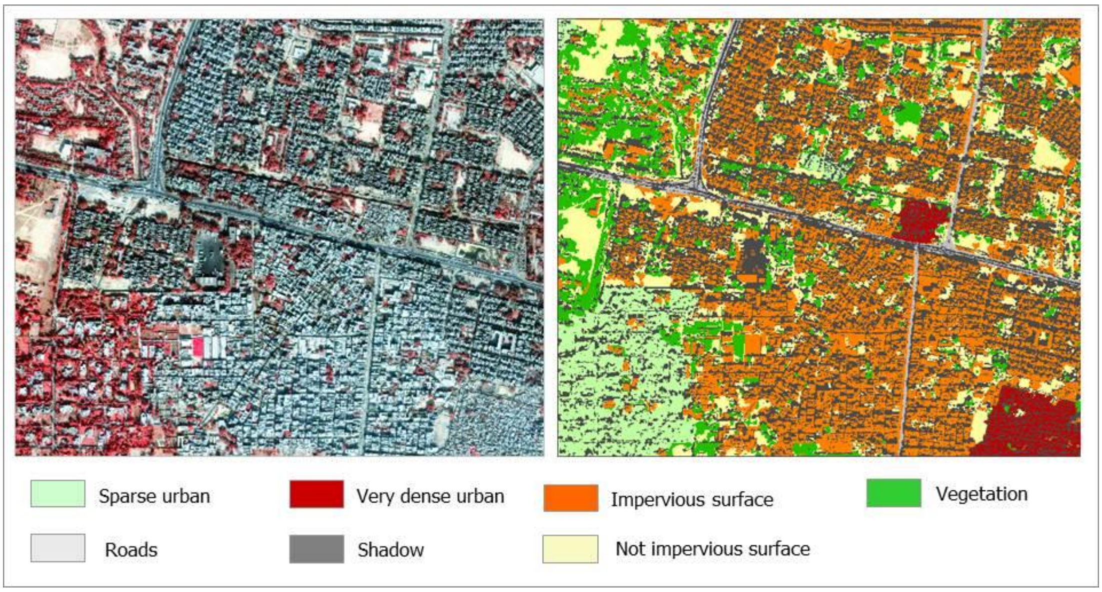

Figure 7-13: Combined classification map of both settlement types – "sparse urban" and "very dense urban" – identified within the fused QuickBird test site South s2 (4/3/2).

As can be observed in Figure 7-13 of course a combined classification map including both identified settlement types – "sparse urban" and "very dense urban" – can be provided as well.

In comparison to the good results of the already successfully classified settlement types, the transfer of the methodology on the remaining on-site defined and during the field campaign mapped settlements "dense urban" and "medium dense urban" figured out to be more complex. Figure 7-14 shows that it is well possible to identify settlement types of these density classes too. For example the "dense urban" settlement *Tughlakabad Extension*, located north and south of the main road, could be separated completely. On the other side it becomes as well apparent, that the quality of the land cover map is slightly lower due to some misclassifications. Difficulties occurred especially in cases where the physical attributes of the sub-objects of two settlement types were very similar (cf. Figure 6-12). For example, a part of the government quarter *Kalkajii DDA Flats* was by mistake classified as "dense urban" this way (west of the north-south-heading main road), even though it should have been classified as "medium dense urban" like the remaining part of the settlement was. A clear and precise separation of the determined settlement types was in this regard hardly possible — not even with an additional adaption of the method, namely the combination of both object-oriented and pixel-based algorithms. It becomes apparent as well that a very detailed street pattern can have an effect on the classification and lead to misassignments (e.g., within the eastern and north-eastern area of the training site).

Figure 7-14: Identification of the settlement types "very dense urban", "dense urban" and "medium dense urban" within the training area included in QuickBird test site South s3 (4, 3, 2). An assignment of the remaining land cover classes was not carried out at this stage in order to be able to better evaluate the quality of the identification of different settlement types.

Misclassifications of course impede the further use of the classification results for subsequent investigations. Therefore the results were in parts manually corrected with in-situ information in order to be usable for the following integrative analysis.

Despite the described problems, all in all, this land cover classification can be regarded as a successful attempt to identify urban settlement structures with very similar physical attributes by means of a (semi-) automatic classification using remote sensing data. This result gives a promising basis for the further enhancements of the methodology developed within this study and for the analysis of remote sensing data in the mega-urban environment.

7.2.3 Quality Assessment of the Classification Results

„The value of the map is clearly a function of the accuracy of the classification."

(FOODY 2002)

Any land cover classification or in general thematic map is, according to their geometrical resolution, basically a generalization of the reality. Such generalization, in turn, evokes some loss of information and so a certain level of incompleteness. That means any mapping process will naturally contain flaws (e.g., FOODY 2002, MALING 1989, and SMITS ET AL. 1999). It is indispensable, consequentially, "that the quality of thematic maps derived from remotely sensed data" need to "be assessed and expressed in a meaningful way" (FOODY 2002). 'Quality' is in this context the equivalent of 'accuracy'. In thematic mapping of remotely sensed data the term accuracy is according to FOODY (2002) "used typically to express the degree of 'correctness' of a map or classification". In essence, classification accuracy determines the degree to which the derived land cover classification conforms to the reality (JANSSEN & VAN DER WEL 1994, MALING 1989, and SMITS ET AL. 1999).

Evaluating the quality of land cover classifications (derived from remotely sensed data) is a very important step in the application, processing and management of remote sensing data. It "has been recognized as a valuable tool in judging the fitness of these data for a particular application" (JANSSEN & VAN DER WEL 1994) and "gives evidence of how well the generated or used classifier is capable of extracting the desired objects from the image" (BAATZ ET AL. 2004). Also an integrated processing of classification data and other types of geodata, as conducted within this study, can only be performed in a responsible way if the quality of the data is known. Hence, the accuracy assessment of the generated land cover classification is also of decisive importance for the continuative analysis of the urban environment of Delhi. Thus, however, accuracy determines at the same time as well the specific value of the resulting image classification to a particular user, i.e. the information value (JANSSEN & VAN DER WEL 1994).

To allow a judgment about the accuracy, land cover maps are in general checked against some ground truth or other reference data (FOODY 2002). Disagreements between the two data sets are generally interpreted as errors in the classification result derived from the remotely sensed data (CONGALTON 1991).

During the last three decades, a large number of papers have been published on accuracy assessment of land cover classification derived from remotely sensed data (cf. ARONOFF 1985, CONGALTON 1991, CONGALTON & GREEN 1999, FOODY 2002, and JANSSEN & VAN DER WEL 1994, ROSENFIELD & FITZPATRICK-LINS 1986). Very different approaches for validation have been presented and discussed in the literature, usually with a particular application in mind for the data in hand (Janssen & van der Wel 1994). Within this study, the land cover classification shall be validated both, in a qualitative and quantitative way.

To verify the results of the classification or settlement differentiation in a qualitative way, the outcomes were checked primarily on the basis of on-site knowledge and photographs taken during the field campaign. As shown in Figure 7-15 the image classification results of a subset of test site South s3 were compared with georeferenced photographs of the respective settlement areas.

Figure 7-15: Qualitative validation of the classification results using photographs taken during the field campaign 2005 (subset of test site South s3): 1 — Jhuggi Jhompri cluster *Nehru* and *Navjeewan Camp* (informal settlement); 2 — *Harijan Colony* (upper lower class to lower middle class) *(Photographs: S. Smollich, October 2005).*

Comparing the photographs with the satellite data and their classification it can be proven that the settlements right and left of the street are strongly different in their appearance. While the houses in the *Nehru* and *Navjeewan Camp* (1) are of very simple style, constructed of different poor and non permanent building materials, the houses in the *Harijan Colony* (2) are already of a more solid construction. Furthermore the settlements are different in their house size or number of stories. The *Nehru* and *Navjeewan Camp* is a representative settlement for substandard housing and inadequate building structures.

Therefore, as the classification result indicates, it is assigned to the informal settlement type. In contrast, the *Harijan Colony* is assigned to the authorized settlement type (resettlement colony) where the residents of the upper lower class and lower middle class live.

In essence, for a first evaluation, this observation can be used to assess the plausibility of the classification result — it supports both, the separation into two different settlement types as well as the localization of informal settlements. But this validation approach is obviously partially subjective and the results can therefore hardly be quantified or even be capable of representing comparable values (BAATZ ET AL. 2004). This method is for example inappropriate if not only the position of different settlement types shall be determined but as well the measurement of the surface coverage is of interest. For a continuative analysis of the urban environment of Delhi, as it is carried out in chapter 8, or for operational applications of the data a visual appraisal of the derived classification results therefore does not fulfil the requirements.

As outlined above, a large number of standard methods are commonly used and recommended in the research literature to quantify the accuracy of thematic land cover data derived from remotely sensed imagery. At present, however, the most widely used methods are based on a *confusion* or *error matrix*[21]. A confusion matrix is a comparison or simple cross-tabulation of the derived (land cover) class label against the one observed in the reference data for a selected number of cases at specified locations (reference points). A confusion matrix contains all the information about relation between classification and reference data and provides therefore an obvious basis for accuracy assessment (BAATZ ET AL. 2004, CANTERS 1997, and FOODY 2002). This basis, in turn, allows for both the characterization of the accuracy of a thematic classification and its errors, which, again, facilitates refining the classification result or estimates derived from it (FOODY 2002). Moreover, different thematic classifications may be compared in terms of their accuracy. There are different measures and statistics that can be derived from the values in a confusion matrix (FOODY 2002, STEHMAN 1997). One of the most popular accuracy measures is the *overall accuracy* — the proportion of all reference pixels which are allocated correctly to the total amount of pixels (in the sense that the class assignment of the classification result and of the reference data coincide) (BAATZ ET AL. 2004, FOODY 2002). Overall accuracy is a measure of the classification as a whole. It contains no information about the classification quality of individual classes (JANSSEN & VAN DER WEL 1994). If attention focuses on the accuracy of individual land cover classes, then *user's*[22] and *producer's accuracy*[23] as

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[21] Within this study, the term 'confusion matrix' is used to indicate the summarized sample results.

[22] The 'user's accuracy' provides the user information about the quality of the land cover data. The measure is calculated by the number of correctly classified samples divided by the row total (JANNSEN & VAN DER WEL 1994).

well as *errors of omission* and *commission* can be calculated (STORY & CONGALTON 1986, JANSSEN & VAN DER WEL 1994). The calculation of these measures, and some other major indices, is given and illustrated by e.g., BAATZ ET AL. 2004, FOODY (2002), JANSSEN & VAN DER WEL (1994) or STORY & CONGALTON (1986). Within this study, using the confusion matrix overall accuracy as well as the producer's and user's accuracy were determined as means of accuracy measures and established for the quality assessment of all classification results (cf. Table 7-1, Table 7-2, as well as Table 7-3 and Table 7-4).

In order to gain more information content out of the confusion matrix than the basic percentage of correctly allocated cases, moreover, Cohen's *Kappa Index of Agreement* (KIA) is determined within this study to express the accuracy of the generated land cover classification (e.g., SMITS ET AL. 1999) (cf. Table 7-1 - Table 7-4). KIA "expresses the proportionate reduction in error generated by a classifier compared with the error of a completely random classification" (MASHEE 2009). Using KIA it is assumed that both land cover classification and reference data are independent class assignments of equal reliability — here the conformity level between the two data sets is what is being measured (BAATZ ET AL. 2004). KIA is often used to compare different classification results in a statistical way and, therefore, to test the effectiveness of different classification methods (that are based on the same data) or the ancillary data applied. Moreover, KIA has the quality to accommodate for the effects of chance agreement and is capable to correct the same (CONGALTON ET AL. 1983, CAMPBELL 1987, BAATZ ET AL. 2004 and FOODY 2002). The calculation of KIA is based on a complete confusion matrix, including information concerning errors of omission and commission (JANSSEN & VAN DER WEL 1994, HUDSON & RAMM 1987). Some authors, such as ROSENFIELD & FITZPATRICK-LINS (1986), "suggest using KIA as a sort of standard measure of accuracy for thematic classifications as a whole" (JANSSEN & VAN DER WEL 1994).

Prior to the description of the realization and the results achieved within this study, a short excursus on sample selection is necessary: Appropriate sample selection, including sampling design and size, is a very important aspect to consider for assessing the accuracy of a land cover classification (FOODY 2002, MASHEE 2009 and NAVULUR 2007). The sampling designs most often used are 'random sampling', 'interval or systematic sampling', 'stratified sampling', 'cluster sampling' as well as 'multistage sampling' (MASHEE 2009 and NAVULUR 2007). Conducting a sample selection some aspects have to be taken into account. For example, a big time gap between the basis data for the reference classification and the data for the classification that shall be evaluated should be avoided. At the same time it is

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[23] The 'producer's accuracy' is calculated dividing the number of correctly classified samples by the column total. "It indicates the percentage of samples of a certain (reference) class, that were correctly classified" (JANSSEN & VAN DER WEL 1994).

essential that the reference classification and the classification that shall be evaluated carry comparable information, which means that they need to have similar classes or at least classes that can be assigned to each other. In addition to that, the pixels need to have the same location and spatial extent on the ground (BAATZ ET AL. 2004).

In the present study, accuracy assessment was calculated using the eCognition software. eCognition^{TM} provides different methods to perform accuracy assessment[24]. Here, the method 'error matrix based on samples' was implemented. This method uses test areas instead of e.g., a complete thematic map as reference data for quality assessment[25]. As test areas samples (i.e. objects, not pixels) derived from manual sample units are considered. It is obvious that it make no sense to use the same sample objects for accuracy assessment as they were already used as training data for the classification process (automatic feature extraction methodology — SEaTH, cf. chapter 6.1.2), as they were assigned to the right class anyway (BAATZ ET AL. 2004). Thus, new sample objects for the calculation of the error matrix have to be created. For this purpose, based on the QuickBird data, an independent interpreter has generated randomly an adequate number of samples for every land cover class. That means, for all derived land cover classification maps one (independent) reference data set is provided to calculate the appropriate accuracy values. Moreover, it is important to say, that in the validation process only segmented QuickBird images with level 1 (scale parameter 5) and classified images as well with level 1 were used.

To deliver a judgment about the quality of the developed (semi-) automated classification method, a confusion matrix for each produced land cover classification map was calculated. First of all, the results for the training area within test site South s3, which was consulted for the development of the approach, is presented in the confusion matrix in Table 7-1. The first column of the table shows the land cover classes that have to be evaluated. In the following columns the number of objects covered by the reference classification (random samples) for each class is displayed. The penultimate column contains the total number of samples for each land cover class assigned by the classification. The sum for each class in the reference classification is given next to last row of the matrix. Moreover, producer´s and user's accuracy are shown in the last column or row respectively. Looking at the values in the confusion matrix a quality assessment of the generated land cover classification compared to the reference classification appears to be feasible (BAATZ ET AL. 2004).

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[24] eCognition^{TM} offers the following four methods for performing accuracy assessment: 'classification stability', 'best classification result', 'error matrix based on TTA mask' as well as 'error matrix based on samples' (BAATZ ET AL. 2004, NAVULUR 2007).

[25] One of the specific problems of mega cities like Delhi is the lack of data for urban planning. This lack of data impedes on the other hand of course the accuracy assessment in these areas as well as no reference data set or thematic GIS map of the respective urban area with suiting or comparable land cover classes is available.

Table 7-1: The confusion matrix for the object-oriented image classification of the training area of test site South s3

		Reference classification							
	User class / sample	Not impervious surface	Roads	Vegetation	Very dense urban	Impervious surface	Shadow	Total	**Producer**** [%]
Land cover classification	Not impervious surface	**86**	11	5	0	50	10	162	53.09
	Roads	11	**180**	1	0	2	4	198	90.91
	Vegetation	24	1	**296**	0	0	6	327	90.52
	Very dense urban	0	0	0	**135**	0	0	135	100.00
	Impervious surface	34	6	4	0	**483**	22	549	87.98
	Shadow	0	0	14	0	0	209	223	93.72
	Unclassified	0	0	0	0	0	0	0	
	Total	155	198	320	135	535	251		
	User* [%]	55.48	90.91	92.50	100.00	90.28	83.27	OA	87.14%***
								KIA	0.837****

*Producer Accuracy: estimates the probability that a sample or pixel which is of *class i* in the reference classification is correctly classified

** User Accuracy: gives information about the probability that a sample or pixel classified as *class i* is actually of *class i*

*** OA — Overall Accuracy: the proportion of all reference pixels which are classified correctly

**** KIA — Kappa Index of Agreement: κ = 1 means perfect agreement between land cover classification and reference data

The comprised accuracy values reveal that the urban landscape of this part of Delhi can be covered with an overall accuracy of around 87 percent. Thus, the overall accuracy of the classification is higher than the commonly recommended 85 percent target. Moreover, typically it is required that in addition to the minimum level of overall accuracy no single class shall be of a lower accuracy than 70 percent (FOODY 2002 and THOMLINSON ET AL. 1999). This benchmark is fulfilled by five out of the total six identified land cover classes. With a producer's and user's accuracy of 100 percent the class "very dense urban" (vdu) and thus informal settlements could be mapped very well within the training area. Hence, the user can rely on the very high probability that a sample classified as "vdu" is in fact "vdu". The situation is different when the remaining classes are considered. Regarding the class "impervious surface" there are 549 samples covered by the impervious samples of the reference classification. 483 of those were classified as "impervious", 50 samples have been assigned to the class "not impervious surface", two samples to the class "roads". This results in a producer's accuracy of 87.98 percent. In contrast, 535 samples were classified in total as "impervious surface", whereof 483 samples were assigned to "impervious surface" as well within the reference classification. The remaining 55 samples were classified as "not impervious" and "shadow". The outcome of this is a user's accuracy of 90.28 percent. This example is well suitable to demonstrate the differences between the appropriate accuracies. While the producer's accuracy tells the interpreter "how well the classification agrees with the reference classification", the user's accuracy gives "information about the probability that a pixel classified as class *i* is actually of class *i* " (BAATZ ET AL. 2004). The classes "roads", "vegetation" as well as "shadow" were classified with comparably high user's accuracies between 83.27 and 92.50 and producer's accuracies between 90.52 and 93.72. Solely the class "not impervious surface", showing a user's and producer's accuracy of 55.48 and 53.09 percent respectively does not fulfill the common requirements for single class accuracy values. Here, only slightly more than 50 percent of the "not impervious" samples of the reference classification are found by the land cover classification. The low user value implicates, in turn, that the user cannot really rely on the classification; as such an object is in almost half of all cases confused with the other classes. Here, not correctly classified objects are mainly misclassified as "impervious surface". Contrawise, as described above, most of the misclassifications of impervious areas are confused as "not impervious". This phenomenon arises from a noticeable speficific criterion of the urban landscape of Delhi — the spectral similiarity of roads, open spaces (not impervious surfaces) as well as many rooftops and other impervious areas.

In order to compensate for the different interests of users and interpreters of the classification result, the Kappa coefficient is added as accuracy value. The KIA for the statistical output in Table 7-1 results in a value of 0.837. This implies that the accuracy of the classification result is around 84 percent better than the accuracy that would result from a random assignment (JANSSEN & VAN DER WEL 1994). According to NAVULUR's (2007) interpretation rules of Kappa values for thematic accuracy assessment this indicates an 'almost perfect' classification result. Nevertheless, the evaluation shows that there is some room for improvement by the classification procedure as well as by repeating the validation process with declaring new or additional reference samples.

The results of the quality assessment for test site South s3 are presented in Table 7-2. The accuracy values within the presented confusion matrix show that using the developed classification approach also a larger urban area of Delhi can be mapped in detail. The overall accuracy value amounts almost 86 percent, and reaches, thus, nearly the value of the training area. Moreover, the target level of 85 percent is exceeded and no single land cover class reveals lower classification accuracy than the required 70 percent. Especially the class "very dense urban" is, again, characterized by high classification accuracy. The KIA value for this test site amounts 0.825.

The transfer of the developed classification methodology to another urban district of Delhi, namely South s2, reaches similar classification accuracies. The accuracy statistics for this test site are shown in Table 7-3. The overall accuracy calculated from the confusion matrix is comparable high or even higher than the values of the previously presented land cover classifications, which implies that the 85 percent target is exceeded. In the transfer classification, moreover, producer's and user's accuracy for all classes were equally high. Regarding the class "very dense urban", being in the focus of the study, producer's and user's accuracies higher than 95 percent are estimated. Only the accuracy values for the class "not impervious surface" are, again, considerably lower than the other classes and the producer's accuracy does not reach the required 70 percent level. Here, the problem is a misclassification with the class "impervious" as previously explained. The Kappa coefficient for the classification of test site South s2 results in a value of 0.87.

Table 7-2: The confusion matrix for the object-oriented image classification of test site South s3

		Reference classification							
	User class / sample	Not impervious surface	Impervious surface	Roads	Vegetation	Very dense urban	Shadow	Total	**Producer**** [%]
Land cover classification	Not impervious surface	**579**	102	39	57	3	43	823	70.35
	Impervious surface	45	**856**	77	39	2	60	1079	79.33
	Roads	18	2	**922**	44	0	41	1027	89.78
	Vegetation	65	2	0	**1768**	0	19	1854	95.36
	Very dense urban	0	0	0	10	**619**	1	630	98.25
	Shadow	0	2	38	168	4	**637**	849	75.03
	Unclassified	0	0	0	0	0	0		
	Total	707	964	1076	2086	628	801		
	User* [%]	81.90	88.80	85.69	84.76	98.57	79.53	**OA**	**85.93%*****
								KIA	**0.825******

*Producer Accuracy: estimates the probability that a sample or pixel which is of *class i* in the reference classification is correctly classified

** User Accuracy: gives information about the probability that a sample or pixel classified as *class i* is actually of *class i*

*** OA — Overall Accuracy: the proportion of all reference pixels which are classified correctly

**** KIA — Kappa Index of Agreement: κ = 1 means perfect agreement between land cover classification and reference data

Applying the developed classification methodology apart from very dense urban areas the settlement type "sparse urban" could successfully be identified within Delhi. According to the confusion matrix in Table 7-4 promising accuracy values could be assessed. In comparison to the previous classifications, producer's and user's accuracy show equally high values for all land cover classes. For example, for the class "sparse urban" a user's accuracy of 87.80 percent and a producer's accuracy of 91.27 percent could be achieved. The target level of 70 percent could thus be reached for this settlement type as well. Hence, it can be stated, that the mapping of this settlement type in Delhi can successfully be performed. However, some loss of quality of the assessment of the class "roads" was noted. Looking at this class there are 309 objects that were classified in total as "roads", whereof 164 samples were also assigned to "roads" in the reference classification. The lion's share (125 samples) of the remaining objects was wrongly assigned to the class "shadow". Obviously the classes "roads" and "shadow" are difficult to separate from each other. This is resulting from the spectral similiarity of both land cover classes in this part of Delhi. This grave misclassification results in a considerably low user's accuracy of only 53.07 percent.

In contrast, for all other land cover classes accuracy values higher than the required 70 percent target were achieved. Hence, the overall accuracy reaches 86.29 percent and the KIA amounts a value of 0.82. This implies that the urban landscape within this area of Delhi can be mapped in detail as well and the land cover map represents an 'almost perfect' classification result (NAVULUR 2007).

Table 7-3: The confusion matrix for the object-oriented image classification of test site South s2 including very dense urban areas

		Reference classification						
	User class / sample	Not impervious surface	Impervious surface	Vegetation	Very dense urban	Shadow	Total	**Producer** [%]**
Land cover classification	Not impervious surface	**521**	194	98	5	3	821	63.46%
	Impervious surface	106	**2278**	29	18	2	2433	93.63%
	Vegetation	58	5	**828**	0	2	893	92.72%
	Very dense urban	0	3	9	**536**	0	548	97.81%
	Shadow	0	20	9	1	**1022**	1052	97.15%
	Unclassified	0	0	0	0	0	0	
	Total	685	2500	973	560	1029		
	User* [%]	76.06	91.12	85.10	95.71	99.32	**OA**	**90.22%*****
							KIA	**0.87** ****

*Producer Accuracy: estimates the probability that a sample or pixel which is of class i in the reference classification is correctly classified

** User Accuracy: gives information about the probability that a sample or pixel classified as class i is actually of class i

*** OA — Overall Accuracy: the proportion of all reference pixels which are classified correctly

**** KIA — Kappa Index of Agreement: κ = 1 means perfect agreement between land cover classification and reference data

(Source: BAATZ ET AL. 2004)

A quantitative assessment of the training area with the simultaneous classification of three settlement types (cf. Figure 7-14) was not attempted due to the not yet sufficient quality or respectively some obvious misclassifications. Some further improvement of the classification methodology appears to be necessary here in order to enable a meaningful quantitative validation.

Table 7-4: The confusion matrix for the object-oriented image classification of test site South s2 including sparse urban areas

		Reference classification							
	User class / sample	Not impervious surface	Impervious surface	Vegetation	Sparse urban	Shadow	Roads	Total	**Producer** [%]**
Land cover classification	Not impervious surface	**581**	113	118	2	2	7	823	70.59
	Impervious surface	92	**1391**	11	37	3	13	1547	89.92
	Vegetation	10	2	**731**	6	0	0	749	97.6
	Sparse urban	0	9	22	**324**	0	0	355	91.27
	Shadow	1	23	9	0	**617**	125	775	79.61
	Roads	0	0	0	0	0	**164**	164	100
	Unclassified	0	0	0	0	0	0	0	
	Total	684	1538	891	369	622	309		
	User* [%]	84.94	90.44	82.04	87.80	99.20	53.07	**OA**	**86.29%*****
								KIA	**0.82** ****

*Producer Accuracy: estimates the probability that a sample or pixel which is of class i in the reference classification is correctly classified

** User Accuracy: gives information about the probability that a sample or pixel classified as class i is actually of class i

*** OA — Overall Accuracy: the proportion of all reference pixels which are classified correctly

**** KIA — Kappa Index of Agreement: κ = 1 means perfect agreement between land cover classification and reference data

(Source: BAATZ ET AL. 2004)

A summary and final judgment of the classification results is presented in the following chapter.

7.2.4 Appraisal of the Classification Results and Summary

Within this study, a classification methodology was developed and conducted to analyze the urban environment of the mega city Delhi. Regarding the complex and heterogeneous appearance of the Delhi area, a semi-automated, object-oriented classification approach, based on segmentation derived image objects, was implemented. The classification process is based on a multi-level fuzzy logic rule base which allows for the integration of a bundle of different object features such as spectral values, shape or texture on different levels. As the complete conceptual framework of this research, the classification methodology was developed based on a smaller representative training area at first and applied to larger test sites within Delhi afterwards.

The object-oriented classification of VHR satellite imagery of the QuickBird sensor allowed for the identification of five urban land cover classes within the municipal area of Delhi: impervious and not impervious areas, vegetation, streets and shadow. In the focus of the image analysis was yet the identification of different settlement types and amongst these the informal settlements in particular. The results presented within this chapter demonstrate, that the developed methodology is suitable to identify different settlement types. Based on density classes the following types could be separated: very dense, dense, medium dense and sparse urban. The developed method appeared to be particularly well suitable for the classification of settlement types with extreme physical attributes. For instance, areas with an extremely high building density and very small building size (very dense urban areas — within this study the equivalent of informal settlements) could be separated out of their environments with a high accuracy within the training site as well as they could clearly be identified within the transfer sites. High accuracy values between around 95 to 100 percent were achieved here.

The classification itself is actually controlled by the selection of the class-dependent criteria and the corresponding thresholds. The quality of the selection of parameters and their thresholds finally influences as well the quality of the classification result and therefore bares certain insecurity, independent of the systematic. Within the present study SEaTH appeared to be a very usefool tool in the context of automatic feature recognition. Using SEaTH, one is able to evaluate statistically any number of given features for the object classes of interest. SEaTH calculates moreover the corresponding, optimum thresholds which allow the maximum separability in the chosen features.

The features identified with the SEaTH tool produce, on the one hand, a very good classification result for the training area and, on the other hand, even a valuable outcome for the transfer sites within the urban area of Delhi. In the given case study for all land cover maps overall accuracies of more than 85 percent could be achieved, which corresponds to the specified target level of 85 percent. Also the accuracy with which the individual land cover classes are mapped ranges mostly above the 70 percent threshold (THOMLINSON ET AL. 1999). All in all, the implemented analyzing tool SEaTH allows for an optimized object-oriented classification which minimizes the misclassified rate and shows promising results in the field of feature recognition for megacity related purposes.

Textural features have turned out within this research to be the decisive image parameter for the identification of the different settlement types and the mapping of the impervious surface areas, whereas mainly spectral parameters act as distinguishing features for land cover mapping of the remaining classes (e.g., vegetation, shadow and street). Hence, the approach takes advantage of both, the extremely high spatial resolution and in addition as well the spectral potential of the used satellite data.

It is a general consensus, that given the premise of transferability, properties with attributes which are as stable as possible in terms of time and space should be considered. Textural features are therefore (in general) better suited to describe different settlement types than spectral properties — at least if the analyst wishes to classify settlement types with similarly observable characteristics in different areas or based on different image data. Spectral attributes show decisively bigger differences between different data sets, and especially between captures of different sensors, than spatial attributes of urban areas. Therefore the question remains open, to which extent the spectral criteria chosen will be stable, once applied to QuickBird data of other mega cities with comparable structural features or to image data of other satellites. The application of the textural parameters on other mega cities is, based on the present experiences, very promising regarding their transferability. In this context further investigations are required (cf. chapter 9).

Despite the convincing results, there are still some limits in the application of VHR remote sensing data regarding the identification of informal settlements. In this research, it was shown that areas with very similar physical attributes, but which are not representing an informal settlement, like urban villages, were assigned to the "very dense urban" land cover class as well. Here, even a visual interpretation of the satellite data will often lead to misclassifications. This means that only the settlement structure itself cannot deliver a reliable classification result. In such cases, in-situ information will always be required to be able to classify such settlements correctly. For the further investigations of this study, as well as for the tasks of urban planners, it is though of decisive interest that all informal settlements are being identified (rather than identifying one settlement too much) and that hence the mapping of this settlement type can be regarded as complete.

Comparable qualitatively valuable results could be achieved as well during the identification of "sparse urban" areas. As informal settlements these areas are characterized as a settlement type with an extreme physical appearance, but in contrast to informal settlements they are characterized by a very low building density, mid-range building size and a large fraction of vegetation. Especially because of their high fraction of vegetation the settlements of the upper class could be separated from their environment very exactly and mapped with high accuracy values (87.8 and 91.3 percent respectively).

Consequentially a limitation of the applied methodology can be observed in the identification of settlement types characterized by missing extreme attributes and by a high level of physical similiarity amongst each other. This is for instance noticeable regarding the results of the transfer of the methodology on the remaining settlement types "dense urban" and "medium dense urban". Here problems occurred mainly since the determination of significant features for optimal class separation and the corresponding thresholds, even with the SEaTH tool, turned out to be difficult. For these settlement types an additional, advanced approach, which combines both object-oriented and pixel-based algorithms, turned out to be more suitable. The classification results indicate that with a combination of both approaches even the identification of "intermediate" settlement types is possible. However, still some enhancements of this methodology seem to be necessary in order to improve the quality of the results, so that the same can be further processed and used for subsequent analysis, without manual adjustments. Nonetheless the results are already now representing a promising basis for the further refinement of the method developed within this study and the analysis of remote sensing image data in the mega-urban environment.

Some further room for improvement can be found regarding the classification of impervious and not impervious surfaces. Referring to the related quality assessment (cf. chapter 7.2.3) various misclassifications between these two classes occured. As these land cover classes are spectrally very similar to each other within Delhi, for an improved future mapping process other spectrally independent characteristics need to be determined and included into the investigations. The limits of this methodology and of the QuickBird data are furthermore reached when single residential buildings within informal settlements shall be delineated. The building density within this settlement type is so high that detecting individual buildings becomes hardly feasible or even unfeasible. For the purpose of this study this deficiency is rather of minor importance though, since the main interest is on general patterns. In fact, the number of residential buildings within a settlement is required for the subsequent integrative analysis, but this information will be derived with another approach which is suitable to compensate this deficit (cf. chapter 8). An improvement in the detectability of single buildings could be achieved by either refining the classification methodology or by the use of other remote sensing data e.g., with higher spatial and/or spectral resolution.

One of the major objectives during the development of the classification methodology (for VHR urban satellite data) was a robust spatial transferability. This means, the approach was meant to be transferred not only to different settlement types within Delhi. But further than this, the rule base was meant to be transferable quickly and easily without many systematic adjustments and with a high classification accuracy to other test sites within the mega city of Delhi. The results within the subchapters above reveal that the developed methodology is fulfilling the requirement of a robust transferability. In general, a rule base is the more transferable, the less it needs to be manually adapted to the specific image characteristics. Within this study, the rule base was transferred successfully and with only little adaptions (mostly adjustment of the threshold values solely) firstly from the training area to another larger test site and then to an additional independent transfer site within the urban area of Delhi. In fact, the classification results of the transfer sites do not reach as high accuracy levels as those of the training site, but they still constantly reach classification accuracies higher than 85 percent. At the same time, the transfer results show that a widespread analysis of urban structures is possible using the applied method. Nevertheless there is still some need for action as until now only a part of the available data and, hence, only a subset of the total urban area was analyzed. The application of the method on the complete set of QuickBird data will be an important objective for future investigations.

All in all, with regard to the results of this research, it can be summarized that the developed object-oriented classification approach represents an effective and flexible approach to analyze VHR QuickBird data. It was shown that even a complex task such as land cover analysis and the identification of different settlement types within a mega urban area can be handled with an appropriate accuracy. The classification results provide therefore an up to date information basis, to examine the potentials and capabilities of remote sensing of urban areas.

It can be further stated that the classification method is able to extract informal settlements from a mega urban environment, as well as to differentiate between different settlement types. Informal settlements represent the most visible expression of urban poverty and are therefore very important for planning strategy.

The outcome of these classifications hence represents a valuable, spatial data basis for further investigations of the heterogeneous urban area of the Indian mega city Delhi. The derived land cover maps form the foundation for the integrative analysis and deliver therefore the possibility to deduce criteria for the evaluation of the living conditions within different settlement types.

The results of the combined application of the remote sensing derived land cover products and socio-economic data is presented in the following chapter.

Chapter 8

Bridging Remote Sensing and Socio-economic Data

The combined application of remotely sensed imagery and socio-economic data for mapping, capturing and characterizing the socio-economic structures and dynamics within the mega city of Delhi is the primary concern of this study. Within the following chapter the results of the integrative use of remote sensing derived data and socio-economic data are presented (cf. chapter 8.1) and the quality of the results is appraised and critically discussed (cf. chapter 8.2).

8.1 Results of the Integrative Data Analysis

In order to derive socio-economic information and thus to characterize the residents' living conditions within certain settlement areas of the mega city of Delhi, first of all several settlement characteristics were estimated from the classified QuickBird data. According to the in chapter 6.2 explained approach, the settlement characteristics "area", "impervious area" as well as "average building size" and "number of houses" were ascertained. The results of the estimation from the classified QuickBird data are presented in Table 8-1. These values are the precondition for the performance of the integrative analysis and therefore for the provision of socio-economic information. Thus, the quality of the calculated values is fundamental for the determination of the population and water related parameters. In order to be able to evaluate the quality of the approach and the results of the subsequent integrative analysis, some validation was carried out. Since no adequate field data for comparative validation is available, a visual counting of houses based on the QuickBird data was undertaken by an independent analyst. This way it is possible to compare the number of counted houses with the number derived from the remote sensing data analysis. Table 8-1 shows that there are only minor deviations in the statistics. The number of houses determined by the remote sensing analysis was overrated for informal settlements by 10 to 19 percent.

Table 8-1: Results of the image data analysis and validation outcomes for selected informal settlements in the mega city of Delhi

	Name of colony	Area (A_S) [m^2]	Impervious Area (A_I) [m^2]	Average House Size (A_H) [m^2]	Number of Houses (N)		
		RS	RS	RS	RS	VC	RS/VC [%]
A	Bhomiheen Camp (subset)	14374.08	10360.80	15	691	608	114
B	Bhomiheen Camp (total)	26925.48	19077.48	15	1272	1130	113
C	Nehru and Navjeewan Camp	84047.04	59153.76	17	3480	2923	119
D	Banjara and Harijan Camp	14749.59	8887.68	19	468	424	110

RS - Analysis of Remote Sensing Data, VC - Visual Counting

(Data source: calculated using remotely sensed QuickBird data)

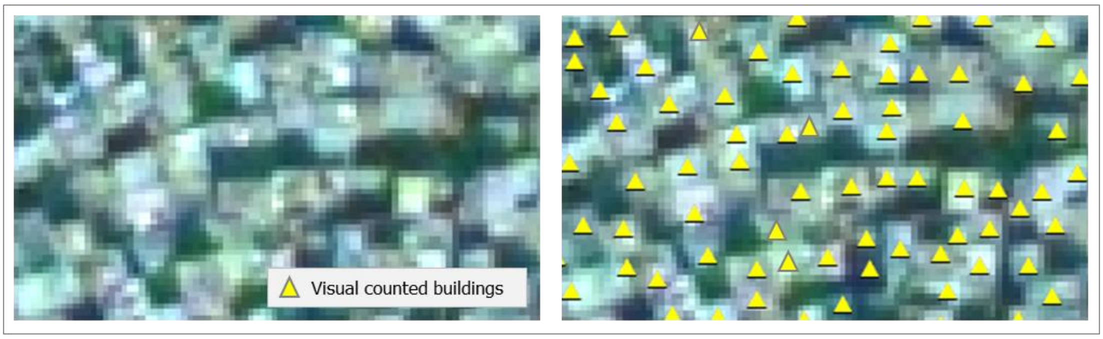

Figure 8-1: Subset of the fused QuickBird test site South s3 (4, 3, 2) versus example for the visual counting process of the buildings within the informal settlement *Bhomiheen Camp*. Primarily the occurrence of shadow and different building materials indicated the differentiation of the buildings.

In order to enhance the plausibility of the accuracy assessment Figure 8-1 is inserted showing an example of the visual counting process of the settlement buildings. Primarily the occurrence of shadow and different construction materials of adjacent buildings indicates the differentiation of the buildings. On closer examination of Figure 8-1 it becomes evident that even a reliable determination of single buildings by visual interpretation of the VHR remote sensing data within this settlement type is very difficult — not to mention a fully automatic extraction using only remote sensing analysis. The buildings are often attached to other buildings, were constructed using a wide variety of materials, and often constructions on the rooftops are covering parts of the roof of single buildings. Moreover a regular street network does not exist, which would evoke some regularity in the building patterns and hence make the extraction of single buildings a lot easier. Accordingly, the fraction of impervious area within the settlement and the mean building size, as reliable parameters, were utilized to determine the total number of houses. With this approach, realistic results of the image data analysis could be provided for the subsequent integrative analysis and therefore for the determination of socio-economic attributes.

Hence, based on the remote sensing derived settlement characteristics an integrative approach by means of ancillary socio-economic in-situ information was developed. The results of the integrative analysis are shown in Table 8-2 as well as in Figure 8-2 and Figure 8-3. Table 8-2 comprises both the final results and the parameters necessary for their derivation. The "Questionnaire" columns (Q) are representing data, where the family size and the water consumption per capita for the different study sites were directly taken from the questionnaires. By means of remote sensing derived settlement parameters, the socio-economic main parameters of interest, "population density" and "total water consumption" could subsequently be calculated. Whereas the columns "Assumption" (As) are reflecting the data which were derived from the representative training area (A) and transferred to the remaining test sites (B, C and D). The remote sensing derived settlement parameters were applied the same way in order to calculate the socio-economic parameters.

Table 8-2: Results of the integrative data analysis for selected informal settlements in the mega city of Delhi

	Name of colony	Family size (F)*		Total population (P)		Population density (D) [Pop./km²]		Water consumption per capita (W_C) [l/d]*		Total water consumption (W_T) [l/d]		
		As	Q	As	Q	As	Q	As	Q	As	Q	As/Q [%]
A	Bhomiheen Camp (subset)	5.43	5.43	3752.13	3752.13	261034.45	261034.45	25	25	93803.25	93803.25	100
B	Bhomiheen Camp (total)	5.43	4.76	6906.96	6054.72	256521.33	224869.53	25	24	172674	145313.28	119
C	Nehru and Navjeewan Camp	5.43	5.45	18896.40	18966.00	224831.24	225659.35	25	16	472410	303456	156
D	Banjara and Harijan Camp	5.43	6.79	2541.24	3177.72	172292.25	215444.63	25	32	63531	101687.04	62

As - Assumption, Q - Questionnaire * Arithmetic Mean

(Data source: calculated using remotely sensed QuickBird data and data from household survey 2005-2006)

The diagrams in Figure 8-2 and Figure 8-3 show a comparison between "population density" and "total water consumption" estimated from the questionnaires (right bars) as well as from the remote sensing data (left bars) for selected areas which represent potential informal settlements. It could be shown that it is generally possible to derive socio-economic data for a larger area, or a comparable second settlement respectively, by a relatively small amount of data collected from a representative training site.

The evaluation of the "population density" results shows that the analysis based on the remote sensing data provides realistic values which correspond not only to the questionnaire data but also to information in the appropriate literature (BRONGER 2004). The informal settlements evaluated in this study are characterized by population density values between 172.000 and 261.000 [Pop./km²]. In Mumbai, population densities higher than 300.000 [Pop./km²] were reported for informal settlements where the living conditions are expected to be even worse than in Delhi (BRONGER 2004).

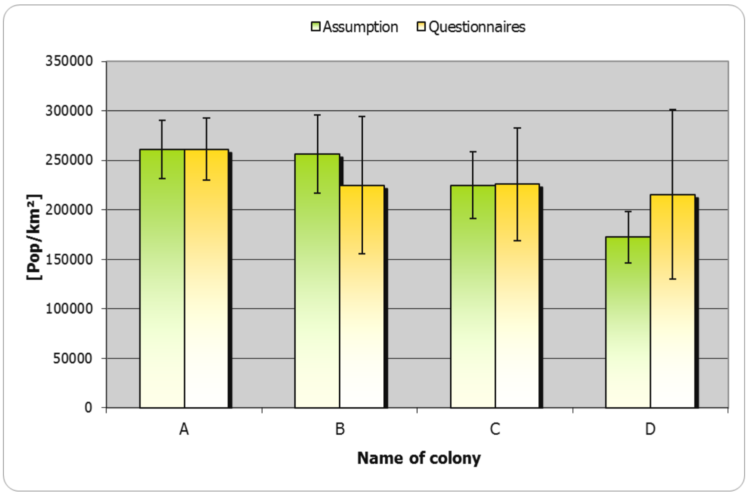

Figure 8-2: Results of the integrative data analysis — population density for four test sites (potential informal settlements) estimated from the questionnaires (right bars) and remote sensing data (left bars): A — *Bhomiheen Camp* (subset), B — *Bhomiheen Camp* (total), C — *Nehru* and *Navjeewan Camp*, D — *Banjara* and *Harijan Camp* *(Data source: calculated using data from household survey 2005-2006).*

Comparing the values of the average population density for the informal settlements with the average population density of whole Delhi or even with the value of Munich for instance (cf. Figure 8-3), it is easily comprehensible that one is talking about settlements with extreme living conditions. The population density of the JJ-colony *Bhoomiheen Camp* for example is 25 times as high as the average of whole Delhi and even almost 60 times as high as the average value of Munich — which is denoted to be the major city with the highest population density in Germany.

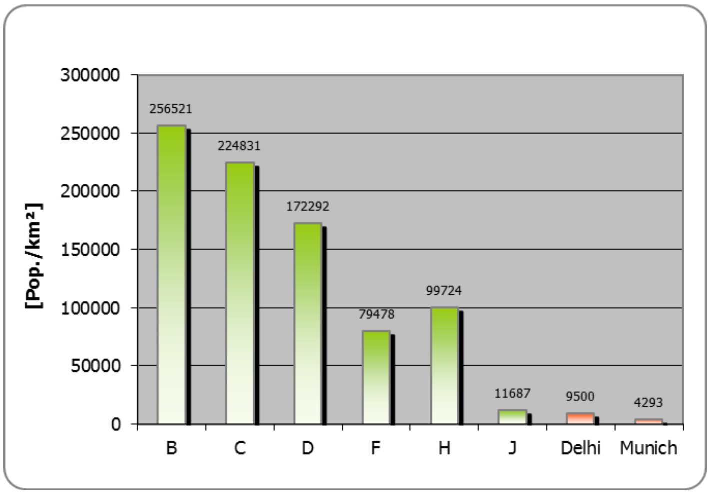

Figure 8-3: Comparison of the population density within different settlements of Delhi, entire Delhi and the city of Munich, Germany: B — *Bhomiheen Camp* (total), C — *Nehru* and *Navjeewan Camp*, D — *Banjara* and *Harijan Camp*, F — *Tughlakabad Extension* (total), H — *Kalkaji DDA Flats* (total), J — *Greater Kailash II*) *(Data source: calculated using data from household survey 2005-2006).*

For the "total water consumption" realistic data could also successfully be derived by means of the integrative data analysis (cf. Figure 8-4). Only the values for the *Nehru* and

Navjeewan Camp (C) show bigger discrepancies. The reason for these discrepancies is on the one hand imprecise information from the interviewed people. As mentioned above, especially the information on the water consumption was often doubtful. An accurate declaration of the inhabitants regarding their water consumption, especially in areas with sporadic water supply, like in the informal settlements, will be difficult to obtain. As these settlements, or single households within the settlements respectively, are not connected to public water supply, the water is provided mostly by public water pumps at irregular intervals. An access to reliable data, based for instance on measurements of water flow meters, is therefore not possible (cf. chapter 2.4 and 5.2.4). This data gap, in turn, shall be closed with the present approach, delivering data for a whole settlement derived from a relatively small amount of in-situ collected information. As it can be seen in Table 8-2, despite the elimination of extreme outliers, the differences between assumption and the questionnaire data were still not negligible. On the other hand, certain deviations resulting from the image classification are possible. And finally the third critical aspect regarding the impreciseness in the data is the determination of the empirical value of 25 [l/d] of mean water consumption per capita derived from the training area. The question here is, whether the selected training area does really deliver representative data as a basis for the calculation of the remaining test sites. In this study the quality of the interview data is the decisive factor for the discrepancies.

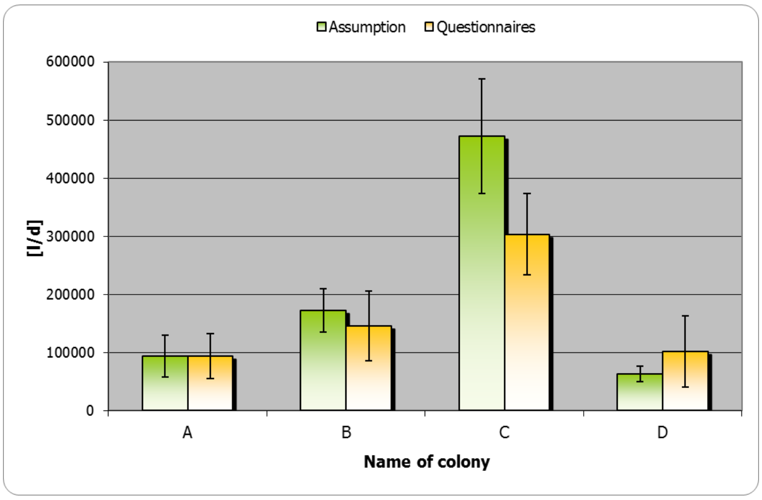

Figure 8-4: Results of the integrative data analysis — total water consumption for four test sites (potential informal settlements) estimated from the questionnaires (right bars) and remote sensing data (left bars): A — *Bhomiheen Camp* (subset), B — *Bhomiheen Camp* (total), C — *Nehru* and *Navjeewan Camp*, D — *Banjara* and *Harijan Camp* *(Data source: calculated using data from household survey 2005-2006)*.

The error bars in the remote sensing values in Figure 8-4 indicate the uncertainties related to the assumptions being made in the data processing (e.g., for number of houses). In order to display the standard deviation, a *Monte Carlo* simulation was performed (METROPOLIS & ULAM 1949). The *Monte Carlo* simulation is just one of many methods for analyzing uncertainty propagation, where the objective is to determine how random variation, lack of knowledge, or error affects the sensitivity, performance, or reliability of the system that is being modeled. A Monte Carlo simulation is categorized as a sampling method because the inputs are randomly generated from probability distributions to simulate the process of sampling from the actual population (METROPOLIS & ULAM 1949). The error bars in the questionnaire data result from outliers (extreme values) in the interview statistics (e.g., for family size or water consumption per family). They are represented within the standard deviation as well.

The deviations between the questionnaire data (Q) and the assumption data (As) regarding the water consumption can be relativized by a comparison with the values for the minimum water supply required as specified by the *World Health Organization* (WHO) (cf. Figure 8-5). The WHO (2003) and other organizations, such as the *National Commission on Urbanization* (1988) or the *Swedish International Water Institute* (FALKENMARK & WIDSTRAND 1992), recommended that a per capita water supply of 80-100 litres per day is required to meet the basic domestic needs, and emphasised that this level of water supply should be ensured to all citizens (RAMACHANDRAIAH 2001). After the *Bureau of Indian Standards* minimum water supply of even 200 litres per capita per day [lpcd] should be provided for domestic consumption in cities (MODI 1998). Considering the fact that various agencies recommend different quantities of requirement of water for domestic use, within this study 100 [lpcd] consumption (here an indication of availability, as consumption is determined by the availability in the case of general shortage) of water is taken as benchmark for identifying water deficient households in the mega city of Delhi. It should be noted here that the selected 100 litres value is no strict requirement level, but it is some kind of average minimum requirement for living with a minimum health and hygiene standard.

It is obvious from Figure 8-5 that in all informal settlements observed in this study, the consumption — as an indication of availability — of water per capita is much lower than what is recommended by the above mentioned organizations. Comparing the results of the integrative analysis with the minimum requirement of 100 [lpcd], the deviation between the assumption and the questionnaire data appears to be almost negligible. In any case a major deficit between the really available and the actually required amount of water can be observed. Regarding the value of 200 [lpcd] announced by the *Bureau of Indian Standards* this deficit is even multiplied. These deductions might not be considerable as absolute but in any case they highlight a tendency which can be taken as a recommendation towards the respective supply organizations (e.g., DJB) and the urban planners. Especially for the supply and development of informal settlements, which are considered as mega urban risk areas and thus potential residential zones of vulnerable population groups, this kind of "support" can be of great help.

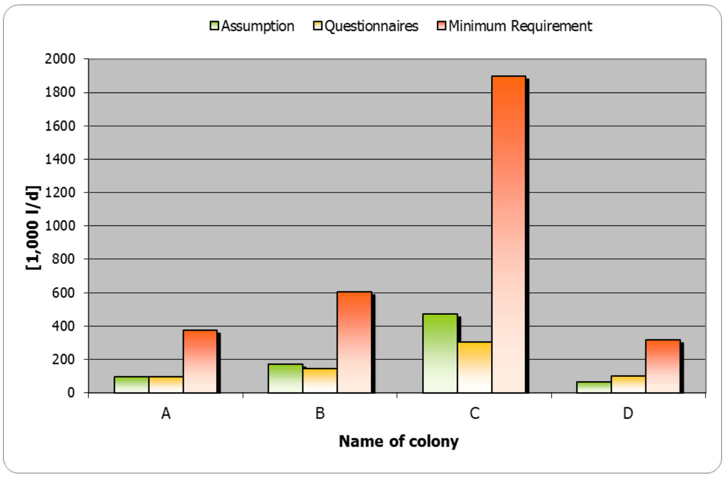

Figure 8-5: Comparison of de-facto water consumption vs. WHO minimum requirement, indicating the deficit in water supply, within different informal settlements in the mega city of Delhi: A — *Bhomiheen Camp* (subset), B — *Bhomiheen Camp* (total), C — *Nehru* and *Navjeewan Camp*, D — *Banjara* and *Harijan Camp* *(Data source: calculated using data from household survey 2005-2006, WHO 2003)*.

Not only for informal settlements within Delhi but also for the remaining settlement types an integrative analysis was performed in order to derive the required socio-economic information and to be able to characterize the living conditions of the inhabitants. Hence, based on the remote sensing derived settlement characteristics (cf. Appendix, Table A.13.1 and A.13.3) and by means of questionnaire derived socio-economic data, like for the informal settlements, the parameters "population density" and "total water consumption" were determined. For a test of the transferability of the methodology, the settlements or test sites indicated as *Tughlakabad Extension* and *Kalkaji DDA Flats* within Map A.14 (cf. Appendix) were selected. These are areas identified as both dense and medium dense urban within the classification process (cf. Figure 7-11). *Tughlakabad Extension* is a partly unauthorised, partly authorised colony of the upper lower and lower middle class characterized by mostly one-family houses. Sometimes small apartments are sublet in order to earn some extra money. In contrast, *Kalkaji DDA Flats* is an authorized middle class residential district (governmental quarter) which is characterized by multi-story dwellings with one apartment per storey. This means that generally one family occupies one storey. Thus, the average number of stories has been considered during the calculation of the "total population" of this settlement (cf. Table A.13.2). For *Tughlakabad Extension* though, one family per building was assumed. For a more detailed characteristic of these settlements please see chapter 4.1 and 4.2.

The diagrams in Figure 8-6 and Figure 8-7 again show a comparison between "population density" and "total water consumption" estimated from the questionnaires (right bars) as well as from the remote sensing data (left bars). It could be shown that it is generally possible to derive socio-economic data for a complete settlement from a relatively small amount of basis data collected in a representative training area.

Figure 8-6: Results of the integrative data analysis — population density for dense and medium dense urban test sites estimated from the questionnaires (right bars) and remote sensing data (left bars): E — *Tughlakabad Extension* (subset), F — *Tughlakabad Extension* (total), G — *Kalkaji DDA Flats* (subset), H — *Kalkaji DDA Flats* (total) *(Data source: calculated using data from household survey 2005-2006)*.

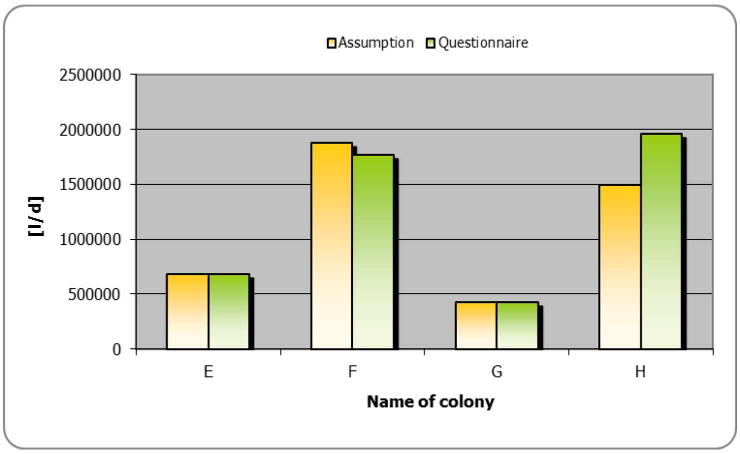

Figure 8-7: Results of the integrative data analysis — total water consumption for dense and medium dense urban test sites estimated from the questionnaires (right bars) and remote sensing data (left bars): E — *Tughlakabad Extension* (subset), F — *Tughlakabad Extension* (total), G — *Kalkaji DDA Flats* (subset), H — *Kalkaji DDA Flats* (total) *(Data source: calculated using data from household survey 2005-2006)*.

In order to compare the housing and supply conditions within the settlements of the lower and middle class with those of the upper class of Delhi, the settlement *Greater Kailash II*, situated in test site South s3, was additionally considered in the investigations[26] (cf. Appendix, Map A.14, as well as Table A.13.3 and A.13.4). *Greater Kailash II* is an authorized, gated community where residents of the lower upper class are living. Since only a relatively small amount of questionnaire data for this settlement is available, the analysis

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[26] The settlement *Sainik Farms* identified as "sparse urban" area could not be included in the analysis as no questionnaire data was available for this area. It was almost impossible to interview residents of the Gated Communities or other quarters of the upper middle class and upper class to collect a numerically equivalent amount of data in the respective settlement types (cf. chapter 5.2).

could not be carried out like for the other settlements by calculating the data for the complete settlement based on data collected for a training area. Instead the methodology was applied directly on the complete settlement. Figure 8-3 shows that the population density within this settlement is with 11,678 [Pop./km²] only slightly higher than the average of Delhi and hence by far lower than the population density within the other investigated areas. The derived value for the "total water consumption" is comparably high. Looking at Figure 8-8, it is obvious that the supply situation, in terms of availability, within this region is by far better than in any of the other examined settlements and even exceeds the average of Delhi. In terms of international comparison, the inhabitants of *Greater Kailash II* even consume more water than the average inhabitant of Munich and hence the availability here definitely exceeds the 100 [lpcd] minimum requirement for domestic use. This information matches the in-situ observations as well as the questionnaire data. The water supply here is provided by private water connections. As the supply is not guaranteed 24 hours a day, partially additional water is purchased in order to cover the daily demands and to irrigate the front yards. The temporal availability of water is a parameter, however, that cannot be analyzed with the present approach. For this purpose, further investigations as well as a qualitative analysis of the living conditions of the inhabitants is necessary, as carried out for the different settlement types of Delhi by SELBACH (2009).

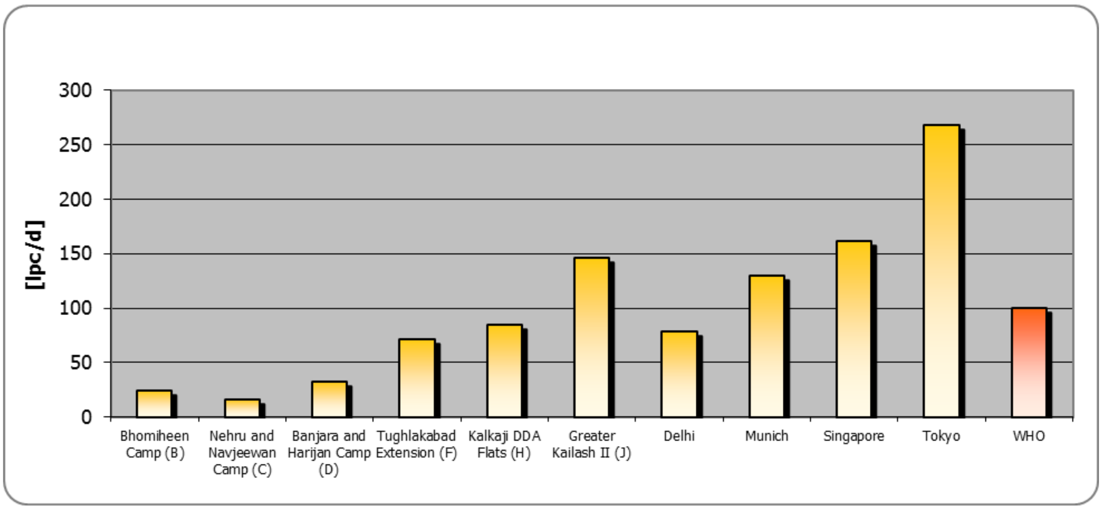

Figure 8-8: Determination of water supply deficit: Comparison of the effective consumption of different settlements in the mega city Delhi (B-J) vs. mean water consumption of Delhi in total, other cities and the minimum requirement of the WHO *(Data source: calculated using data from household survey 2005-2006, DOWN TO EARTH 2005, WHO 2003).*

This comparison shows on the other side as well that in the majority of the examined settlements of Delhi the conditions appear to be critical, especially in the informal settlements and unplanned unauthorized areas (e.g., *Tughlakabad Extension*). In this context, it is surprising to find Delhi's average water consumption to be so low, when at the same time the Delhi Jal Board (DJB) claims supplying, on average, 211 [lpcd]. Solely in the residential areas of the upper middle and lower upper class the water availability is adequate and achieves the required benchmark of 100 [lpcd]. Comparable studies within Delhi point out that about 72 percent of the households consume less than 100 [lpcd] and almost 30 percent even have less than 50 [lpcd] available (SHABAN 2008).

8.2 Summary and Appraisal of the Combined Use of Remotely Sensed Imagery and Socio-economic Data

Since the physical appearance in urban environments is a reflection of human activity, an isolated examination of social questions without considering geospatial questions does neither meet the requirements of social science nor the requirements of remote sensing. Hence, urban remote sensing has the potential to represent a valuable interdisciplinary platform for social and physical science (cf. chapter 3.3 and 3.4). Against this background, the linking of remote sensing and social science shall be pushed forward in the course of this research study. A methodology was developed to compensate the lack of in-situ collected socio-economic data by means of remote sensing imagery together with the integration of few questionnaire data in order to allow an indirect assessment of the living conditions of the inhabitants in different settlement types in the mega city of Delhi (cf. chapter 6.2).

In the following, the results of this integrative analysis are summarized and the quality of the developed approach as well as the benefit of the derived information is examined.

The remote sensing derived land cover maps (cf. chapter 7.2) form the basis for the integrative method and were therefore embedded in the analysis concept (cf. chater 6.2). The following settlement characteristics were successfully estimated from the classified QuickBird data and used to derive spatial information about the population distribution (cf. chapter 8.1):

- Area of the settlement,
- Impervious area,
- Fraction of impervious area (sealing degree),
- Average building size, and
- Number of houses.

In addition to the remote sensing derived data, the integrative approach makes use of socio-economic data derived from georeferenced questionnaires (conducted during two field trips in Delhi, cf. chapter 5.2). This was used to characterize a given settlement type in terms of specific population and water related variables. Here, the following parameters, necessary for the integrative assessment, could be achieved (cf. chapter 8.1):

- Family size,
- Mean water consumption per capita, and
- Mean water consumption per family.

Finally, the remote sensing derived data were combined with the questionnaire derived information in order to achieve criteria for the evaluation of the living conditions within different settlement types. The evaluation of the results showed that it is possible to characterize a given settlement type – in this case, an informal settlement – in terms of specific population and water related parameters (cf. chapter 8.1):

- Total population,
- Population density, as well as
- Total water consumption.

In turn, these outcomes, if compared for example with the population average data of the whole city or with the water consumption values specified by the WHO, enable an identification of living quarters of vulnerable population and, therefore of potential risk areas within the mega city of Delhi.

In order to compare the housing and supply conditions of the inhabitants living in the different settlement types appearing in Delhi, the developed integrative analysis approach was transferred from the informal settlements (very dense urban areas) to the remaining settlement types (dense and medium dense urban) within the mega city. The performance has demonstrated that it is also possible to characterize the living quarters of the middle and upper class within the mega city of Delhi, and, hence, to assess and classify the living conditions of the local inhabitants.

Solely regarding the settlement type "sparse urban" the integrative analysis could not be applied, because for these areas the required questionnaire data was not available. In light of the experiences of this study, a transfer of the method to this settlement type would as well be promising though. In such cases — where the inhabitants of the respective settlement type being reluctant to answer questionnaires or household surveys being generally impossible due to different reasons — an analysis without questionnaire data would be a possible alternative. Here estimations based on general or experiental knowledge could be used in order to substitute the survey data. As generally no absolute quantitative information can be derived with this method, but rather tendencies and trends shall be determined, such an approach could well be taken into account.

Since the settlement type "sparse urban" represents residential areas of the upper class of Delhi were the living conditions and the economic status are comparably high, no real need for action is required here anyway. Urban planners and other persons in charge are not necessarily depending on additional socio-economic information, which is the reason why the missing integrative analysis of this settlement type does not negatively affect the quality of this study.

Considering the methodology of indirect data assessment developed within this study and its results, (out of the perspective of governmental agencies, urban planners or other persons in charge) the following benefits in comparison to a non-integrative analysis (i.e. conventional approach) can be summarized:

- One of the most obvious and direct benefits of the developed methodology is the transferability. The possibility to transfer the method from one settlement type to another as well as the transfer of the method itself from one test site within the megacity to another was successfully demonstrated within this research.

- In comparson to the conventional mapping and data ascertainment procedures in mega urban areas, the developed integrative analysis can be applied in a time and cost saving way. In contrast to highly elaborate and costly total in-situ ascertainments, using this approach only a relatively small amount of socio-economic data in form of collected questionnaires is required. Hence, on the one hand much fewer man power is needed which leads to drastically less labor costs[27]. Even with the purchasing of the satellite data taken into account, the cost factor could considerably be reduced. On the other hand, a spatially comprehensive in-situ data assessment is highly time consuming and can even taken some years for such complex areas as a mega city. The acquisition of the questionnaire data required for the development of the integrative method could be completed within approximately two months, which is significantly quicker than any conventional method. Contingently it could be considered to even completely abstain from a partial data acquisition as carried out within this study. It is theoretically possible to solely refer to experience information for the deriving of the socio-economic data, which would in turn speed up the whole process even more.

- Regarding a repeated application of the integrative method after a certain time, the time benefit of this method becomes out of above explained reasons even more relevant in comparison to a repetition of a total in-situ data assessment. Once the method is robust (in terms of its reliability), it can be applied in a randomly or regularly repeated way. For such a repeated application of the integrative method, some minor adaptations of the classification parameters and their thresholds may be necessary. The reason for this are rather the image specific attributes of the new remote sensing data than difficulties occurring during the systematic adaptation process. The process of the integrative analysis itself remains unchanged. A regular repeatability of the method finally enables even the monitoring of a certain district or of the complete urban area which would be impossible with in-situ data acquisition. By this means, the persons in charge can be significantly and scientifically supported in their strategical planning and resulting measures.

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[27] Whereas this criterion cannot be considered as the decisive factor due to low wages in developing and threshold countries.

- An additional advantage, which is directly linked with the quick and repeatable application, can be seen in the timeliness, with which certain questions can be handled using the developed methodology. Diverse remote sensing sensors can deliver very up to date images of a specific area of investigation. The acquired remote sensing data can theoretically be delivered to the customer within only few days after the date of its acquisition. In addition to that, as already mentioned, only few in-situ data is required, which can be collected within a relatively short period of time. This leads to an all in all very low response time for the derivation of socio-economic data within urban areas, whereas a conventional data acquisition cannot at all satisfy this requirement of actuality. Taken to extremes this could mean, that the results of a conservative in-situ acquisition will not be available before they are already out-dated. This is even the more valid, when dealing with a complex and highly dynamic urban area as the mega city Delhi. Due to the repeatability of the developed method, the actuality of a respective analysis can even be kept up to date (cf. previous paragraph).

- The integrative aproach using remotely sensed data arises furthermore the potential to analyze wide areas in one application. By means of remote sensing data, especially satellite-based imagery, large-scale analysis are possible capturing enormous areas like for example large parts or even the complete urban area of mega cities like Delhi. Within this study, the approach was developed for one training site and then transferred to two complete test sites successfully.

All in all, the listed benefits are very convincing and corroborate the combined use of remotely sensed and socio-economic data in mega city research. It is important to once again mention that the developed method does not call for absolute quanitative correctness but rather shows up tendencies in the urban development of a mega city.

In the following the developed approach and its results shall be discussed critically. Some facts are pointed out, which have to be included in the examination and appraisal of the developed integrative analysis method. The derivation of socio-economic information out of structural attributes of the urban morphology is generally transferable to all examined test sites within Delhi. The accuracy of the results is depending on the one hand on the quality of the physical parameters determined from the remote sensing data, and consequentially of the quality of the derived land cover maps (cf. chapter 7.2.3 and 7.2.4). On the other hand, the accuracy of the results is depending on the quality of the household survey and the quantity of questionnaire data for the respective settlements.

Appraising the quality of the physical parameters derived from the remote sensing data, especially one aspect needs to be discussed critically. A fully automatic determination of the average building sizes per settlement type would naturally be more independent of the image interpreter and therefore of course be preferable to a semi-automatic method. Still this will only be possible, when all single buildings can be separated by the classification process. Here, especially for the analysis of very dense urban areas, as the informal settlements in Delhi, the interpretation of remote sensing data today still reaches its limits (cf. chapter 7.2.4).

Regarding the quality of the household survey, for example the missing homogeneity of the sampling within the test sites, i.e. the differing quantitiy of questionnaires per settlement, needs to be discussed critically. Moreover, the correctness and plausibility of a certain fraction of the answers of the respondents (of all question types and in all settlements) need to be doubted out of different reasons. Consequently a certain error ratio was taken into account. While the information regarding the family size can generally be regarded as reliable, the answers concerning the water consumption need to be scrutinized (cf. chapter 5.2.4). Here it is mainly the poor educational background of the respondents as well as a lack of water meters[28], which resulted partially in answers that must be doubted in principle. Because this problem of partially unreliable data occurs in the same way for any complete survey or census, this fact cannot be seen as a disadvantage of the developed integrative method. It is important to mention here, that due to this problem the results regarding the water consumption related to the residents of the different settlements are to be interpreted as a tendency and not as universally valid, quantitative representative data. Uncertainties in the remote sensing derived data as well as in the questionnaire data were represented within the standard deviation indicated using error bars. A detailed evaluation and discussion of the quality of the household survey and the collected quantitative socio-economic information is already included in a previous chapter of this work, please refer to chapter 5.2.4.

Besides the amount of available water one needs to analyze some additional criteria, if the water supply of specific inhabitants shall be evaluated. Of high importance for the affected persons are the quality and the times of availability as well as the reliability of the supply. All these factors can of course not be considered in the developed quantitative and on remote sensing data based method, but rather have to be examined separately with a qualitative approach (cf. SELBACH 2009).

These facts considered, it can be stated as an interim conclusion that remote sensing data together with an integrative approach are more suitable to derive population parameters of a mega city than information regarding the water consumption.

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[28] Informal settlements generally are not attached to the municipal water supply system. Because no tab water is available, of course no water meters are present either.

Chapter 9

Final Conclusions and Outlook

This closing chapter summarizes the results, achievements and constraints of this study. It aims to evaluate the validity of the working hypotheses and to answer and appraise the crucial questions raised in the introduction (cf. chapter 1). Moreover, it examines the outcome of this work in a wider context leading to an outlook on future potentials of remote sensing in urban areas in general and on the here developed integrative approach in particular.

9.1 What has been achieved? – Conclusion

With regard to the working hypotheses and the corresponding research questions raised in the introducing chapter of this thesis (cf. chapter 1.1), some major conclusions can be drawn:

- **The living conditions of the residents are reflected in the settlement structure of the mega cities.**

Already during the on-site inspection and the selection of the test sites as well as during the extensive in-situ data collection and the household survey it could be noticed that different settlement types have developed within Delhi, where in direct neighborhood most heterogeneous living conditions can be observed. This observation was confirmed by the evaluation of the questionnaire data (cf. chapter 5.2), which collected quantitative and qualitative information about the socio-economic background. Socio-economic variables, such as family size, water supply and disposal or health care — which decisively characterize and influence the life and the living conditions of the inhabitants — were inquired and analyzed in order to investigate how the inhabitants of the different settlement types in Delhi in fact really are. It could clearly be determined that a direct correlation exists between the settlement type and the living conditions of the inhabitants. This correlation was in some degree expected and is not really surprizing. Thinking of informal settlements for instance, it is quite easy to imagine that the inhabitants here are faced with overcrowding, insufficient basic infrastructure and a lack of health care. The living conditions themselves and the corresponding attributes, which were questioned in order to evaluate the same, are not directly measurable from outside though. Yet, it was shown within this work that they are in direct correlation to physical attributes as for example building size and density or the fraction of vegetation. This correlation at the same time corroborates the thesis that the individual living conditions of the residents visibly affect the structure of their settlement within the mega city of Delhi. This, in turn, implies that it is in deed possible to assess by a visual observation of a settlement from outside how the people living inside the settlement are. This approach benefits from the fact that the heterogeneity of the living conditions is extreme, the development within direct neighborhood can be contrary, and hence the visible contrasts within the settlement structure are strongly pronounced which is a typical characteristic of mega cities especially in developing countries (cf. chapter 2.3).

In order to further follow the developed approach, the second working hypothesis needed to be investigated:

- **The settlement structure of mega cities is reflected in remote sensing images.**

Following to the definition of the test sites and the in-situ assessment of the socio-geographic general conditions, the potentials of remote sensing in the mega urban environment in general and for Delhi in particular were examined. A review of previous and current research and developments in urban remote sensing was carried out (cf. chapter 3) and in particular already existing remote sensing data was analyzed for one concrete example. In the course of this study, a classification methodology was developed and conducted to analyze the urban landscape of the mega city Delhi. Regarding the complex and heterogeneous appearance of the Delhi area, a semi-automated, object-oriented classification approach, based on segmentation derived image objects, was implemented (cf. chapter 7). Like the complete conceptual framework of this research, the classification methodology was developed based on a smaller representative training area at first and applied to larger test sites within Delhi afterwards.

Already during the visual examination of the sattelite data it became obvious that the on-site observed physical parameters, that were discribed above, and therewith the settlement structures are clearly reflected in the remote sensing data. This, in turn, showed great promise for the development of an adequate classification algorithm.

The classification of very high resolution satellite data enables a prompt and up to date analysis of mega urban structures. The potential of this type of data first and foremost can be seen in the derivation of physical parameters and their spatial distribution. The results of this study and their critical discussion emphasize the capabilities of QuickBird data and of the VHR remote sensing data in general for (mega) urban environments. QuickBird data is especially well suitable for the mapping of urban land use, as it particularly fulfills the small-scale requirements demanded by the highly structured urban landscape due to its very high spatial resolution. The object-oriented classification methodology developed within this research allowed for the identification of five urban land cover classes within the municipal area of Delhi. For all land cover maps overall accuracies of more than 85 percent could be achieved (cf. chapter 7.2.3). The achieved results show with a high level of accuracy the correct class, their spatial distribution and number of occurrences within the overall land cover. Even if the derived maps from a city planer's point of view do not deliver data, qualitatively sufficient for cadastral land register, they do deliver from a remote sensing point of view data of a high to very high level of precision representing a reliable and profound basis for further analysis.

The postulated hypothesis that the settlement structures are reflected in remote sensing data can hence be considered as proven.

After the validity of the above described approach had been veryfied, the different settlement types appearing within Delhi were moved into the focus of this study (cf. chapter 1.1):

- **It is possible to identify settlements within a mega city by analyzing remote sensing data where the living conditions are particularly poor and where therefore is direct need for action.**

While analyzing the image data the identification of different settlement types in general, and amongst these of informal settlements in particular was in the focus. The results presented within this work demonstrate, that the developed methodology is generally capable to identify different settlement types. In total, four different settlement types could be identified. The developed method appeared to be particularly well suitable for the classification of settlement types with extreme physical attributes. On the basis of their building density, building size, and fraction of vegetation (i.e., their physical parameters), especially "very dense urban" areas — within this study the equivalent of informal settlements — and "sparse urban" areas (living quarters of the upper middle class and the upper class) could be separated out of their environments with a very high accuracy (cf. chapter 7.2.3). Whereas the identification of settlement types characterized by missing extreme visible attributes and by a high level of physical similarity amongst each other showed less accurate results. A clear and precise separation of the remaining on-site defined settlements "dense urban" and "medium dense urban" was in fact hardly possible. An adaption of the classification method, namely the combination of both object-oriented and pixel-based algorithms, delivered more precise results, which nonetheless could not reach the level of accuracy of the other results.

Despite the described problems, the general results of the land cover classification can be regarded as a successful attempt to map and differentiate between different settlement types within a mega urban environment by means of a (semi-) automated assignment using remote sensing data. This result opens a promising perspective for further enhancements of the methodology developed within this research and for the analysis of remote sensing data in the mega-urban landscape.

Especially the identification of informal structures where the living conditions are particularly poor and where therefore is direct need for action are very important and useful for planning strategy. Informal settlements are the most visible expression of urban poverty in developing world cities (cf. chapter 2.4). Since dwellers here are exposed to a high degree of many sorts of risk, a reaction of urban management appears to be more than necessary especially for these areas. Often such areas are not recognized and addressed by the public authorities as an integral or equal part of the city, which is one of the reasons why the data base of informal settlements and their dwellers is mostly insufficient. However, especially the physical entities of informal settlements can, as a result of the social circumstances the inhabitants live in, be detected from remote sensing data quite clearly and can thus be extracted from a mega urban environment with comparably low efforts. Hence the developed approach has the potential to support the authorities to react and step into action, where their intervention is most urgently needed.

- **Remote sensing provides the opportunity to detect, observe and assess complex spatial patterns of urban structures.**

All in all, with regard to the results of this research, it can be summarized that the developed object-oriented classification approach represents an effective and flexible method to analyze VHR QuickBird data. But how big is the potential of remote sensing in the specific field of mega city research? It was shown that even a complex task such as land cover analysis and the identification of different settlement types within a mega urban area can be handled with an appropriate accuracy. The remote sensing derived land cover maps (cf. chapter 7.2) form the basis for the integrative method and were therefore embedded in the analysis concept (cf. chapter 6.2). The classification is capable to provide an up to date information basis, to examine the potentials and capabilities of remote sensing of urban areas.

Besides the classification itself, remote sensing can provide data for various dependent attributes associated with human activity – first and foremost the environmental impacts of numerous social, demographic or economic processes (cf. chapter 3.3). Hence, the surveillance and monitoring of land cover may visualize the fingermarks of urbanization. Moreover, the derivation of other specific physical parameters is possible, like: "area of the settlement", "impervious area" and "fraction of impervious area", "average building size", and "number of houses". These settlement characteristics were successfully assessed from the classified QuickBird data and used to derive information about the spatial distribution of the population (cf. chapter 8.1).

The quality of the land cover classification hence is of crucial importance for this approach as misclassifications directly influence the subsequent calculations and consequently distort the aforementioned parameters. The semi-automated classification method provides the derivation of objective, and thus mostly from visual interpretation independant results. The potential of remote sensing can hence be fully utilized, which is advantageous in many aspects in comparison to an interpretation by the human eye. All in all, with the help of VHR satellite data, a more cost-effective, area-wide and up to date information basis was generated for the permanently dynamically changing environment of Delhi.

- **The settlement structure acts as an interface between remote sensing and social science in mega city research.**

The physical appearance of urban landscapes is a reflection of human activity. An isolated examination of social questions detached from geospatial questions does therefore neither meet the requirements of social science nor the requirements of remote sensing. Thus, urban remote sensing has the potential to be an important meeting point for social and physical scientists (cf. chapter 3.3). Today, the urban remote sensing community is still at the beginning of integrative work, the researchers are here still in the early stages of development. Even if the linking of remote sensing and social science may bear difficulties and still is in the early stages of its development, it has already gained in importance and still continues to expand its field of application. This thesis jumps here on the moving train and aims to push the potential of remote sening for social and physical scientists working together. Against this background, a joint approach linking social science and remote sensing was the keystone for this research study. In order to compensate the lack of in-situ collected socio-economic data by means of remote sensing imagery together with the integration of few questionnaire data a methodology was developed allowing an indirect assessment of the living conditions of the inhabitants in different settlement types in the mega city of Delhi (cf. chapter 6.2).

Between the two disciplines, the settlement structure was identified as the bridging element that on the one hand is visible in the remote sensing data and on the other hand is directly correlated to the living conditions of the inhabitants.

- **It is possible by means of remote sensing data (and by including socio-economic data) to reveal information about the living conditions of urban dwellers.**

Based on the land cover derived settlement characteristics (physical attributes) and the socio-economic data derived from georeferenced questionnaires the integrative approach allows for an assessment of socio-economic parameters like: "total population amount", "population density", and "total water consumption".

It was shown, that it is possible with a relatively small amount of questionnaire data for a representative training area, to derive sufficiently exact socio-economic information for (significantly) larger areas and for all mapped settlement types in the investigation areas of Delhi. The methodology could moreover successfully be transferred to all examined test sites within Delhi, whereas the accuracy of the derived information was of course depending on the quality of both, the physical parameters defined from the remote sensing data, and consequentially of the derived land cover maps, and on the other hand on the quality of the questionnaires processed.

Still even in cases where the required questionnaire data is of insufficient quality or is even not available due to different reasons, in light of the experiences of this research, an analysis without questionnaire data at all appears to be possible. Accepting a certain loss of accuracy, it may be an option in future to abstain from questionnaire data in order to avoid the often difficult and time- and labour-intensive data acqusition in-situ. However, the participation of social scientists will still be essential as here once again there expertise and their specific knowledge about the region of interest will be of decisive importance.

All in all, the developed integrative analysis method enables the derivation of up to date, large-areas-covering and in their dimension correct socio-economic information for the highly dynamic urban area of the mega city of Delhi. The derived information, together with the results of the land cover mapping, form a profound and promising basis for the actual estimation of the living conditions of the inhabitants of the different settlements within this mega city. Thus, the methodology developed presents a promising alternative or a reasonable supplement to the elaborate and time-consuming surveys and mapping campaigns on site.

This conclusion already anticipates the answer to the last hypothesis of this work:

- **Remote sensing has the potential to be used as a "social measuring instrument".**

One of the most important findings of the performed integrative analysis (cf. chapter 8) and of this thesis in general is that the contribution of remote sensing to urban planning and management goes beyond mapping the objects of the built environment alone. Interpreting and evaluating remotely sensed imagery rather enables scientists to provide uniquely useful information for social research.

Methods that link results of remote sensing observation with ground-based social data have the capability to improve the understanding of the parameters of different land use changes and therefore of developments in the urban environment. Thus, the using of remotely sensed data has the potential to measure social phenomena and their effects.

Additional, up to date information about the living space and the living conditions of the inhabitants do not only educate the public awareness but can as well support the decision makers and urban planners in mega cities with a highly dynamic of urban growth to develop suitable strategies, effective measures or preventive actions for a healthy urban development.

In this regard, the most obvious and direct beneficiaries are on the one hand the governmental agencies and urban planners and on the other hand, and which is possibly the most important aspect, the inhabitants of the affected areas, whose living conditions can be monitored and improved as required. Only if the urban monitoring is quickly, inexpensively and easily available, it will be accepted and applied by the authorities, which in turn enables for the poorest to get the support they need.

9.2 What remains to be done? – Outlook

This study introduced a number of new and relevant findings that both promote the existing knowledge of mega city research in general and that supplements the current state of research in the field of urban remote sensing in particular. Looking from far away on the Earth´s surface down to the household level, this thesis has introduced certain new insights regarding the satellite based investigation of the living conditions of slum dwellers and their neighbors living side by side in a mega city like Delhi.

The present study presents, on the one hand, a semi-automated object-oriented classification approach which allows for, using VHR remote sensing data alone, the identification and distinction of different settlement types within the complex urban area of Delhi, India. Since informal settlements represent those characteristic municipal areas which are subject to particularly high dynamics, population density as well as marginalization, the research was focused on this settlement type. In combination with socio-economic data, on the other hand, the mapping results were successfully embedded in an integrative analysis concept in order to provide indicators to identify socio-economic structures and their dynamics. In this context, primarily information on population and water related parameters were successfully derived. However, this research needs to be understood as a first step to the development of a new transferable methodology for the identification and analysis of urban structures within mega cities like Delhi.

Consequentially based on the results of this research and the findings derived in this study regarding the limiting factors as well as the derived answers to the key questions of this thesis (cf. Chapter 9.1) a wide field of potentials regarding the further development opens up regarding on the one hand the developed mapping method as well as on the other hand the integrative, i.e. the cross-disciplinary research work.

The results of this investigation show clearly that a large-scale analysis of urban structures is possible applying the developed method. One of the most interesting future challenges lies now in the transferability of the developed methodology. Until now only a part of the available satellite (as well as socio-economic) data and, hence, only a subset of the total urban area of Delhi was analyzed. In order to substantiate the robustness of the developed methodology the application on the remaining test sites (cf. chapter 5.1) (and therefore on other urban areas and settlement types) or even on the complete set of available QuickBird data would be an important objective for further investigations.[29] Based on the knowledge, gained within this study, a transfer on other Indian mega cities, e.g. Mumbai or Calcutta, seems to be very promising as well. In addition, the transfer of the developed methodology to other mega cities in developing countries with similar physical structures would be very interesting and promising. In growing Asian mega cities as Dhaka (Bangladesh) or Jakarta (Indonesia) both the robustness of the mapping method and the interdisciplinary approach could with the utmost probability be tested and could most likely make a contribution to previous and current investigations within these mega cities (e.g., GRÜBNER 2011).

Based on the developed integrative analysis method up to date, large-areas-covering and in their dimension correct socio-economic information for the highly dynamic urban area of the mega city of Delhi could be derived. Socio-economic parameters like "total population amount", "population density", and "total water consumption" could be assessed with high

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[29] While considering the transfer of the method to wider test areas in Delhi or even to complete QuickBird scenes the processing time must not be disregarded. Not least due to the high computing time for the segmentation relatively small test sites had been selected. By upscaling these to a multiple, the computing time of the data sets will despite of the fixed parameter settings multiple too, even up to several days.

precision. In order to upgrade the amount of investigated socio-economic information and thus of the assessment of the living conditions of the people living in mega cities a transfer of the integrative approach to other socio-economic parameters would be desirable. Relatively easily conceivable would be a transfer to personal and water related parameters already imposed by the survey within the framework of this research project like "income" (per capita/family), "level of education" , "number of diseases" (per capita/family per year) or "amount of wastewater" (per capita/family). Of course, this would be a very valuable contribution to the information already available. Naturally a transfer to diverse other socio-economic parameters, not imposed within this project is imaginable as well. At best, the required information can be delivered by the urban decision makers, so that a time-consuming and cost-intensive survey is not required.

Appraising the quality of the physical parameters derived from the remote sensing data, especially one aspect was discussed critically (cf. chapter 8.2). A fully automatic determination of the average building sizes per settlement type would naturally be more independent of the image interpreter and therefore of course be preferable to a semi-automatic method. However, this will only be possible, when all single buildings can be separated by the classification process. Here, especially for the analysis of very dense urban areas, as the informal settlements in Delhi, the interpretation of remote sensing data today still reaches its limits. Hence, a reliable detection of single residential buildings within informal settlements is a crucial step in order to reach a next level of automation of the approach. Concerning this matter it will be necessary to either improve the current classification approach or other remote sensing data will be required. In this context, the major potential of further development appears to be in alternative, new VHR remote sensing data. The latest and current developments show both, a geometric and spectral optimization in comparison to the QuickBird data used in this research. For instance, satellite systems like the 2007 launched Geo-Eye-1 (URL 19) implement with a spatial resolution of 41 cm for the panchromatic band a higher precision of geometric resolution. Especially the 2009 launched sensor WorldView-2 (URL 20) with a spatial resolution of 50 cm panchromatic and an extension of the spectral range in the medium and thermal infrared to now 8 bands (1.85m ms resolution) raises expectations of new potentials in the precision of (semi-) automated extraction of information. The same applies for WorldView-3 (URL 20) – the first multi-payload, super-spectral, high-resolution commercial satellite. Launched in 2014, WorldView-3 provides 31 cm panchromatic resolution, 1.24 m multispectral resolution, and 3.7 m short-wave infrared resolution (cf. Figure 3-1).

Besides the optical data, as well radar data show capabilities in the analysis of urban areas (SOERGEL 2010). Radar remote sensing has in contrast to optical remote sensing the advantage to be independent of weather and daylight. Satellite missions like the German TerraSar-X or the Canadian Radarsat-2 deliver today a comparable geometric resolution to optical systems (e.g., ESCH ET AL. 2013, TAUBENBÖCK ET AL. 2012). Still, until today radar sensors are not yet really capable to deliver relevant data for urban structure analyses. Besides the optical sensors, they might as well become more important data sources for urban remote sensing in the future though and hence their introduction into this field might become an additional potential of improvement within nearer future.

The diversity of available data and the steadily ongoing technical progress are generating more and more options and potentials how to further develop the approach presented within this thesis. Another interesting field of investigation to be mentioned here are time series. Using satellite data with proceeding acquisition date, change detection analysis is possible. Such analysis can for example derive information about the permanent change and development of certain districts of interest of the mega city of Delhi. Especially for this thesis time series of spatial information about informal settlements would be of interest, for instance to which extent the settlements have grown, become smaller or even disappeared.

As mentioned before, the classification of informal settlements was particularly well possible with the developed method. Informal settlements could be separated out of their environments with a very high accuracy within the training site as well as they could clearly be identified within the transfer sites. Generally the classification method delivered good results for settlement types with extreme physical attributes, which are not only informal settlements but for instance as well areas of the category "sparse urban". In contrast a limitation of the applied methodology was observed in the identification of settlement types characterized by missing extreme attributes and by a high level of physical similarity amongst each other. This was for instance noticeable regarding the results of the transfer of the methodology on the remaining settlement types "dense urban" and "medium dense urban". Even though the classification results delivered by an additional, advanced approach, which combines both object-oriented and pixel-based algorithms, turned out to be more suitable, still some enhancements of this methodology seem to be necessary in order to improve the quality of the results, so that the same can be further processed and used for subsequent analysis, without manual adjustments. Hence, the direct transfer of the developed methodology on the remaining "intermediate" settlement types figured out to be less successful. An aim of further investigations should therefore be the simplification of the determination and structure of the classification parameters in order to easily and quickly enable the application to other settlement types as well as to other test sites or other mega cities (with comparable structures) respectively or even to other satellite data. In the first instance the method of combined object- and pixel based approach should be refined. This approach is still in its early stage of development but delivers very promising results. During such refinement especially the exploitation of the spectral capabilities should be optimized, which in turn describes a link to the already mentioned new VHR sensors with optimized spectral and geometric attributes. A transfer of the method to these data logically seems to be promising.

However neither the good transferability (robustness), nor further enhancements of the method nor the diversity and quality of new generation remote sensing data will be of great benefit, if the access to the required data for the analysis of interest is not given. Of great importance for applied research scientists in this field is an as easy as possible and continuous access to already available and up to date satellite data. A rethinking in the data policy would be eligible in order to relieve the access to up to date data and to reduce the cost for its acquisition. The European program *Copernicus*, previously known as GMES (Global Monitoring for Environment and Security) (URL 21) makes a big step in the right direction. Copernicus stands for the establishment of a European capacity for Earth Observation and the Copernicus space component aims to ensure comprehensive and sustainable supply of data from space-based Earth observation.

While discussing the access and quality of data one should especially against the background of the here developed integrative approach not only focus on the remote sensing data. As the appraisal of the survey data in this integrative study showed, the quality and quantity of the socio-economic data are as well decisive factors for the results of such interdisciplinary analysis. For the approach applied in this research no free of charge accessible data were available, so that an elaborate field survey had to be conducted. The cooperation with persons in charge as urban planners or managers plays an important role and has great potential for comparable studies, as they are often the only source of up to date and reliable data which can be used as supplementary data or in terms of validation of the analysis results. Due to the fact that the results of such analysis are primarily useful for their planning, the cooperation with the urban planners and managers is generally eligible. Good results again convince the decision makers of the value of the applied method, which will in turn lead to a mutual acceptance and willing cooperation.

The developed method delivers the basis for the monitoring of the mega city of Delhi or certain areas within the city respectively by remote sensing. The opportunity to capture the condition of a mega city and to monitor its development in general enables the persons in charge to identify unbeneficial trends and to intervene accordingly from an urban planning perspective and to countersteer against a non-adequate supply of the inhabitants of different urban districts, primarily of those of informal settlements.

Should the responsible managers succeed in reducing the proportion of slum inhabitants or non-adequately supplied dwellers, by giving them the possibility to live self-reliantly and to earn their income themselves instead of creating cost for the municipal authorities, the city itself and therewith the whole urban population of the mega city will develop positively.

The enormous opportunities of the global urbanization process for a sustainable development can only be realized, if the economic integration organized in an ecologically compatible and socially fair way (HEINRICHS 2010). In this spirit, the words of the anonymous slum inhabitant of Delhi, which was cited at the very beginning of this thesis, is not only true for himself as an affected person but becomes valid for the whole community and the city in principle. Without meaning it, he made a statement which is true for himself, his own mega city Delhi and possibly even any other mega city in this world: "It's expensive to be poor"!

Chapter 10

Bibliography

Abdollahi, K.K. & Z.H. Ning (2000): Urban vegetation and their relative ability in intercepting particle pollution (PM2.5). In: *Urban Environment*, vol. 3, American Meteorology Society (AMS), pp. 127-128.

Addink, E.A., de Jong, S.M. & E.J. Pebesma (2007): The Importance of Scale in Object-based mapping of vegetation parameters with Hyperspectral imagery. In: *Photogrammetric Engineering and Remote Sensing*, vol. 73, pp. 905-912.

Ahuja, R. (2006): Das Dickicht indischer Megastädte. Eine Annäherung. In: Ahuja, R & C. Brosius (eds.): *Mumbai — Delhi — Kolkata. Annäherung an die Megastädte Indiens.* Draupadi Verlag, Heidelberg, 310 pp.

Akbari, H., Pomerantz, M. & H. Taha (2001): Cool surfaces and shade trees to reduce energy use and improve air quality in urban areas. In: *Solar Energy*, vol. 70, no. 3, pp. 295-310.

Alkan, M., Marangoz, A.M. & S. Karakis (2008): Feature Extractions from High Resolution Imagery and Using For City Information System. In: *Proceedings of 4th Workshop on Remote Sensing for Developing Countries / GISDECO 8*, 4-7 June 2008, Istanbul, Turkey, 9 pp.

Albertz, J. (2001): Einführung in die Fernerkundung. Grundlagen der Interpretation von Luft- und Satellitenbildern. Wissenschaftliche Buchgesellschaft, Darmstadt, 2nd ed., 249 pp.

Alobeid, A. & K. Jacobsen (2008): Automatic generation of digital surface models from Ikonos stereo imagery and related application. In: *GORS, 16th International Symposium "Remote Sensing and Spatial Information"*, 10-12 November 2008, Damascus, Syria, 8 pp., URL: http://www.ipi.uni-hannover.de/publikationen_abt1.html (access September 2009).

Anderson, J.R., Hardy, E.E., Roach, J.T. & R.E. Witmer (1976): A land use and land cover classification system for use with remote sensor data. A revision of the land use classification system as presented in U.S. Geological Survey Circular 671. In: *Geological Survey Professional Paper 964*, Washington, 41 pp.

Anderson, S.J., Tuttle, B.T., Powell, R.L. & P.C. Sutton (2010): Characterizing relationships between population density and nighttime imagery for Denver, Colorado: issues of scale and representation. In: *International Journal of Remote Sensing*, vol. 31, pp. 5733-5746.

Aniello, C., Morgan, K., Busbey, A. & L. Newland (1995): Mapping micro-urban heat islands using Landsat TM and GIS. In: *Computers & Geosciences*, vol. 21, no. 8, pp. 965-967.

Aplin, P. (2003): Comparison of simulated IKONOS and SPOT HRV imagery for classifying urban areas. In: Mesev, V. (ed.): *Remotely Sensed Cities*. Taylor & Francis, London, New York, pp. 23-45.

ARONOFF, S. (1985): The minimum accuracy value as an index of classification accuracy. In: *Photogrammetric Engineering & Remote Sensing*, vol. 51, pp. 99-111.

ATZBERGER, C. (2004): Object-based retrieval of biophysical canopy variables using artificial neural nets and radiative transfer models. In: *Remote Sensing of Environment*, vol. 93, pp. 53-67.

AZAR, D., GRAESSER, J., ENGSTROM, R., COMENETZ, J., LEDDY JR, R.M., SCHECHTMAN, N.G. & T. ANDREWS (2010): Spatial refinement of census population distribution using remotely sensed estimates of impervious surfaces in Haiti. In: *International Journal of Remote Sensing*, vol. 31, pp. 5635-5655.

BAATZ, M. & A. SCHÄPE (2000): Multiresolution segmentation: an optimization approach for high quality multi-scale image segmentation. In: STROBL, J. & T. BLASCHKE (eds): *Angewandte Geographische Informationsverarbeitung XII. Beiträge zum AGIT-Symposium Salzburg 2000*, Wichmann Verlag, Heidelberg, pp. 12–23.

BAATZ, M. & M. MIMLER (2002): Bildobjekt-Primitive als Bausteine — Extraktion von Objekten „of interest" bzw. anthropogenen Objekten basierend auf der expliziten Kanteninformation von Bildobjekt-Primitiven. In: BLASCHKE, T. (ed.): *Fernerkundung und GIS*. Wichmann Verlag, Heidelberg, pp. 179-188.

BAATZ, M., BENZ, U., DEHGHANI, S., HEYNEN, M., HÖLTJE, A., HOFMANN, P., LINGENFELDER, I., MIMLER, M., SOHLBACH, M., WEBER, M. & G. WILLHAUCK (2003): *eCognition User Guide 3: Object oriented image analysis*, Definiens Imaging GmbH, Munich, Germany.

BAATZ, M., BENZ, U., DEHGHANI, S., HEYNEN, M., HÖLTJE, A., HOFMANN, P., LINGENFELDER, I., MIMLER, M., SOHLBACH, M., WEBER, M. & G. WILLHAUCK (2004): *eCognition User Guide 4: Object oriented image analysis*, Definiens Imaging GmbH, Munich, Germany.

BALLING, R.C. & S.W. BRAZELL (1988): High resolution surface temperature patterns in a complex urban terrain. In: *Photogrammetric Engineering and Remote Sensing*, vol. 54, pp. 1289-1293.

BALTSAVIAS, E.P. & A. GRUEN (2003): Resolution convergence: a comparison of aerial photos, LIDAR and IKONOS for monitoring cities. In: MESEV, V. (ed.) (2003): *Remotely Sensed Cities*. Taylor & Francis, London, New York, pp. 47-82.

BANERJEE, B. (2002): Security of tenure in Indian cities. In: DURAND-LASSERVE, A. & L. ROYSTON (eds.): Holding their Grounds. Secure Land tenure for the Urban Poor in Developing Countries. Earthscan, London, pp. 37-58.

BANZHAF, E., KINDLER, A. & D. HAASE (2007): Monitoring, Mapping and Modelling Urban decline: A Multi-Scale Approach for Leipzig, Germany. In: *EARSeL eProceedings*, vol. 6, no. 2, pp. 101-114.

BARNSLEY, M.J. & S.L. BARR (1996): Inferring urban land use from satellite sensor images using kernel-based spatial re-classification. In: *Photogrammetric Engineering and Remote Sensing*, vol. 62, no. 8, pp. 949-958.

BARNSLEY, M.J. & S.L. BARR (1997): A region-based, graph-oriented data model for the inference of second order information from remotely-sensed images. In: *International Journal of Geographical Information Science*, vol. 11, no. 6, pp. 555-576.

BATRA, B.J. (2005): Entitlement to Services and Amenities in JJ clusters, JJ Relocation Colonies and other non-planned settlements in Delhi: an Overview. Ensuring public accountability community action 2005, Institute of Social Studies Trust, New Delhi, 20 pp. URL: http://www.isst-india.org/PDF/Entitlement%20to%20Services.pdf (access February 2009).

BAUD, I., KUFFER, M., PFEFFER, K., SLIUZAS, R. & S. KARUPPANNAN (2010): Understanding heterogeneity in metropolitan India: The added value of remote sensing data for analyzing sub-standard residential areas. In: *International Journal of Applied Earth Observation and Geoinformation*, vol. 12, pp. 359-374.

BAUER, T. & K. STEINNOCHER (2001): Per parcel land use classification in urban areas applying a rule-based technique. In: *GeoBIT/GIS*, no. 6, pp. 24-27.

BEN-DOR, E., LEVIN, N. & H. SAARONI (2001): A spectral based recognition of the urban environment using the visible and near-infrared spectral region (0.4-1.1 µm). A case study over Tel-Aviv, Israel. In: *International Journal of Remote Sensing*, vol. 22, no. 11, pp. 2193-2218.

BENZ, U., HOFMANN, P., WILLHAUCK, G., LINGENFELDER, I. & M. HEYNEN (2004): Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. In: *ISPRS Journal of Photogrammetry & Remote Sensing*, vol. 58, pp. 239-258.

BETTENCOURT, L. M. A., LOBO, J., HELBING, D., KÜHNERT, C. & G. B. WEST (2005): Growth, innovation, scaling, and the pace of life in cities. *Proceedings of the National Academy of Science of the United States of America (PNAS)*, vol. 104, no. 17, pp. 7301-7306. URL: http://www.pnas.org/content/104/17/7301.full.pdf+html (access July 2008).

BHASKARAN, S., PARAMANANDA, S. & M. RAMNARAYAN (2010): Per-pixel and object-oriented classification methods for mapping urban features using Ikonos satellite data. In: *Applied Geography*, vol. 30, no. 4, PP. 650-665.

BHATTA, B. (2010): Analysis of Urban Growth and Sprawl from Remote Sensing Data. Springer, Berlin, Heidelberg, 192 pp.

BHATTACHARYYA, A.A. (1943): On a measure of divergence between two statistical populations defined by their probability distributions. In: *Calcutta Math. Soc.*, vol. 35, pp. 99-110.

BING, Z., JIANGU, L., XIANGJUN, W. & W. CHANGSHAN (1998): Study on the Classification of Hyperspectral Data in Urban Area. In: *SPIE*, vol. 3502.0277-786x/98.

BISHOP, C.M. (2006): *Pattern Recognition and machine Learning* (Information Science and Statistics), Springer, New York, 738 pp.

BOCHOW, M., SEGL, K. & H. KAUFMANN (2006): Potential of Hyperspectral remote Sensing Data for the Automated Mapping and Monitoring of Urban Biotopes. In: *Proceeding of 1st Workshop of the EARSeL-SIG Urban Remote Sensing "Urban Remote Sensing, Challenges and Solutions"*, 2-3 March 2006, Berlin, Germany, 7 pp.

BOSE, A. (1980): *India's Urbanization: 1901-2000*. Tata McGraw Hill, 2nd edition, New Delhi.

BOTHE, H. (1993): Fuzzy Logic — Einführung in die Theorie und Anwendung. Springer, Berlin, New York, pp. 226.

BOWDEN, L.W. (1975): Urban environments: inventory and analysis. In: BOWDEN, L.W. & E.L. PRUITT (eds.): *Manual Remote Sensing*, 1st Ed., American Society of Photogrammetry, pp. 1815-1880.

BRADBURN, N., SUDMAN, S. & B. WANSINK (2004): Asking Questions. The Definitive Guide to Questionnaire Design — For Market Research, Political Polls, and Social and Health Questionnaires. John Wiley & Sons, San Francisco, revised edition, 448 pp.

BRANCH, M.C. (1971): *City Planning and Aerial Information*. Harvard University Press, Cambridge, Mass, 302 pp.

BRONGER, D. (1994): Indiens Megastädte: Fluch oder Segen? In: GORMSEN, E. & A. THIMM (eds.): *Megastädte in der Dritten Welt*. Veröffentlichungen des interdisziplinären Arbeitskreises „Dritte Welt", vol. 8, Mainz, pp. 11-44.

BRONGER, D. (1996): Megastädte. *Geographische Rundschau*, vol. 48, no. 2, pp. 74-81.

BRONGER, D. (2004): *Metropolen, Megastädte, Global Cities. Die Metropolisierung der Erde*. Wissenschaftliche Buchgesellschaft, Darmstadt, Germany, 216 pp.

BROWN, M.E., GRACE, K., SHIVELY, G., JOHNSON, K.B. & M. CARROLL (2014): Using satellite remote sensing and household survey data to assess human health and nutrition response to environmental change. In: *Population and Environment*, vol. 36, no. 1, pp. 48-72, DOI: 10.1007/s11111-013-0201-0.

BUDER, W. (1998): Zwei Strategien zur Landschaftsanalyse: CIR-Biotoptypen- und Landnutzungskartierung und selektive terrestrische Biotopkartierung. In: SÄCHSISCHE AKADEMIE FÜR NATUR UND UMWELT (ed.): Ergebnisse der CIR-Biotoptypen – und Landnutzungskartierung und ihre Anwendungsmöglichkeiten in der Naturschutzpraxis, vol. 3, pp. 21-24.

CAMPBELL, J.B. (1987): *Introduction to Remote Sensing*. The Guilford Press, New York, London, 551 pp.

CAMPBELL, J.B. (2002): Introduction to Remote Sensing. Taylor & Francis, New York, 3rd edition, 552 pp.

CAMPS-VALLS, G. & L. BRUZZONE (eds.) (2009): *Kernel Methods for Remote Sensing Data Analysis.* John Wiley & Sons, 1st ed., Chichester, 434 pp.

CANTERS, F. (1997): Evaluating the uncertainty of area estimates derived from fuzzy land-cover classification: In: *Photogrammetric Engineering and Remote Sensing*, vol. 63, pp. 403-414.

CANTY, M.J. (2006): Image Analysis, Classification and Change Detection in Remote Sensing. Taylor & Francis, New York, 368 pp.

CARLEER, A.P. & E. WOLFF (2006): Urban land cover multi-level region-based classification of VHR data by selecting relevant features. In: *International Journal of Remote Sensing*, vol. 27, no. 6, pp. 1035-1051.

CARLSON, T.N., AUGUSTINE, J.A. & F.E. BOLAND (1977): Potential application of satellite temperature-measurements in analysis of land-use over urban areas. In: Bull. Am. Meteorol. Soc., vol. 58, no. 12, pp. 1301-1303.

CENSUS OPERATIONS (2001): Census of India 2001. Series 8. Provisional Population Totals. Paper 2 of 2001. Rural – Urban Distribution of Population. Delhi.

CENTENO, J.A.S. & M.A. MIQUELES (2004): Extraction of Buildings in Brasilian Urban Environments Using High Resolution Remote Sensing Imagery and Laser Scanner Data. In: *Proc. ISPRS Conference*, 12-23 July 2004, Istanbul, 4 pp.

CHAN, J.C.-W., CHAN, K.-P. & A.G.-O. YEH (2001): Detecting the nature of change in an urban environment: A comparison of machine learning algorithms. In: *Photogrammetric Engineering and Remote Sensing*, vol. 67, pp. 213-225.

CHANG, N.-B. & Z. XUAN (2012): Spatiotemporal Interactions among Soil Moisture, Vegetation Cover, and Evapotranspiration in the Tampa Bay Urban Region, Florida. In: CHANG, N.-B. & Y. HONG (eds.): *Multiscale Hydrologic Remote Sensing. Perspectives and Applications.* Taylor & Francis Group/CRC Press, Boca Raton, FL, USA, 568 pp.

CHEN, S., ZENG, S. & C. XIE (2000): Remote Sensing and GIS for Urban Growth Analysis in China. In: *Photogrammetric Engineering and Remote Sensing*, vol. 66, pp.593-598.

CHEN, X.-L., ZHAO, H.-M., LI, P.-X. & Z.-Y. YIN (2006): Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes. In: WENG, Q. & D.A. QUATTROCHI (eds.): *Remote Sensing of Environment, vol. 104, Special Issue on Thermal Remote Sensing of Urban Areas*, pp. 133-146.

CHEN, K. (2007): An approach to linking remotely sensed data and aerial census data. In*: Int. Journal of Remote Sensing*, vol. 23, no. 1, pp 37-48.

CHEN, N. & L. HELIGMAN (1994): Growth of the World's Megalopolises. In: FUCHS, R. J. ET AL. (eds.): *Mega-city Growth and the Future*. United Nations University Press, Tokyo, New York, Paris, pp. 17-31.

CHENG, J. (2003): Modelling Spatial & Temporal Urban Growth. Doctoral Dissertation, Faculty of Geographical Sciences, Utrecht University, ISBN 90-6164-212-4, 203 pp.

CHENG, J. & I. MASSER (2003): Urban growth pattern modelling: a case study of Wuhan city, PR China. In: *Landscape and Urban Planning*, vol. 62, pp. 199-217.

CHENG, P., TOUTIN, T. & Y. ZHANG (2003): QuickBird — Geometric correction, data fusion, and automatic DEM extraction. *Earth Observation Magazine*, vol. 11, no. 4, pp. 14-18.

CITIES ALLIANCE (1999): *Cities Without Slums: Action Plan For Moving Slum Upgrading to Scale*. World Bank/UNCHS (Habitat), Washington DC, 23 pp.

CLAPHAM, JR. W.B. (2001): Continuum-based classification of remotely sensed imagery to describe urban sprawl on watershed scale. In: *Remote Sensing of Environment*, vol. 86, no. 3, pp. 322-340.

COCKS, T., JENSEN, R., STEWART, A., WILSON, I. & T. SHIELDS (1998). The HyMap Airborne Hyperspectral Sensor: the System, Calibration, and Performance. In: SCHAEPMAN, D., SCHLAPFER, D. & K.I. ITTEN (eds): *Proceedings of the "1st EARSeL Workshop on Imaging Spectroscopy",* 6–8 October 1998, Zurich, Switzerland, pp. 37-42.

CONGALTON, R.G., ODERWALD, R.G. & R.A. MEAD (1983): Assessing Landsat Classification Accuracy Using Discrete Multivariate Analysis Statistical Techniques. In: *Photogrammetric Engineering and Remote Sensing*, vol. 49, no. 12, pp. 1671-1678.

CONGALTON, R.G. (1991): A review of assessing the accuracy of classifications of remotely sensed data. In: *Remote Sensing of Environment*, vol. 37, pp. 35-46.

CONGALTON, R.G. & K. GREEN (1999): Assessing the accuracy of remotely sensed data: principles and practices. Lewis Publishers, Boca Raton, FL, 137 pp.

COWEN, D.J., JENSEN, J.R., BRESNAHAN, G., EHLER, D., TRAVES, D., HUANG, X., WEISNER, C. & H.E. MACKEY (1995): The Design and Implementation of an Integrated GIS for Environmental Applications. In: *Photogrammetric Engineering & Remote Sensing*, vol. 61, pp. 1393-1404.

COWEN, D.J. & J.R. JENSEN (1998): Extraction and Modeling of Urban Attributes Using remote Sensing Technology. In: LIVERMAN, D., MORAN, E.F., RINDFUSS, R.R. & P.C. STERN (eds.): *People and Pixels. Linking Remote Sensing and Social Science*. National Academy Press, Washington, D.C., pp. 164-188.

COY, M. & F. KRAAS (2003): Probleme der Urbanisierung in den Entwicklungsländern. *Petermanns Geographische Mitteilungen*, vol. 147, no. 1, pp. 32-41.

CRANE, P. & A. KINZIG (2005): Nature in the Metropolis. *Science*, vol. 308, p. 1225.

CUSHNIE, J.L. (1987): The interactive effects of spatial resolution and degree of internal variability within land-cover types on classification accuracies. In: *International Journal of Remote Sensing*, vol. 8, no.1, pp. 15-29.

DAMM, A., HOSTERT, P. & S. SCHIEFER (2005): Investigating urban railway corridors with geometric high resolution satellite data. In: MOELLER, M. & E. WENTZ (eds.): *Proceedings of the ISPRS Joint Symposium URBAN 2005 and URS 2005*, 14-16 March 2005, Tempe, AZ, 5 pp.

DARWISH, A., LEUKERT, K. & W. REINHARDT (2003): Urban land-cover classification: An object based perspective. In: *Proc. of 2nd GRSS/ISPRS Joint Workshop on Data Fusion and Remote Sensing Over Urban Areas*, Berlin, Germany, pp. 278-282.

DAVIS, F.W. & D.S. SIMONETt (1991): GIS and remote Sensing. In: MAGUIRE, D.J., GOODCHILD, M.F. & D.W. RHIND (eds): *Geographical Information Systems: Principles and Applications*. Longman, London, pp. 191-213.

DAVIS, M. (2006): Planet of Slums. London, New York, 240 pp.

DAUREAU, F., BARBARRY, O., MICHEL, A. & B. LORTIC (1989): *Area Sampling from Satellite Image for Socio-Demographic Surveys in Urban Environments*. Editions de l'ORSTOM, Paris, 15pp.

DE FRIES, R.S. & J. CHEUNG-WAI CHAN (2000): Multiple criteria for evaluating machine learning algorithms for land cover classification from satellite data. In: *Remote Sensing of Environment,* vol. 74, pp. 503-515.

DEGG, M. (1992): Natural Disasters: Recent Trends and Future Prospects. In: *Geography*, pp. 198-209.

DELL'AQUA, F., GAMBA, P., IODICE, A., LISINI, G., RICCIO, D. & G. RUELLO (2003): Simulation and Analysis of Fine Resolution SAR Images in Urban Areas. In: *Proc. 2nd GRSS/ISPRS Joint Workshop "Data Fusion and Remote Sensing over Urban Areas"*, 22-23 May 2003, Berlin, Germany, pp. 133-136.

DE JONG, S.M., BAGRÉ, A., VAN TEEFFELEN, P.B.M. & W.P.A. VAN DEURSEN (2000): Monitoring Trends in Urban Growth and Surveying City Quarters in the City of Ouagadougou, Burkina Faso Using SPOT-XS. In: *Geocarto International*, vol. 15, no.2, pp.61-68.

DE KOK, R. (2001): Objektorientierte Bildanalyse. Ein Lösungsansatz für den automatisierten Einsatz sehr hochauflösender Satellitendaten für forstliche Fragestellungen. Doctoral Dissertation, Faculty of Forestry, Technical University (TU) Munich, Germany.

DOBSON, J.E. (1993): Land cover, land use differences distinct. In: *GIS World*, vol. 6, no. 2, pp. 20-22.

DOBSON, J.E., BRIGHT, E.A.,COLEMAN, P.R., DURFEE, R.C. & B.A. WORLEY (2000): LandScan: A global population database for estimating population at risk. In: *Photogrammetric Engineering & Remote Sensing*, vol. 66, pp. 849-857.

DONNAY, J.-P. (1999): Use of remote sensing information in planning. In: STILLWELL, J., GEERTMANN, S. & S. OPENSHAW (eds): *Geographical Information and Planning*, Springer Verlag, Berlin, pp. 242-260.

DONNAY, J.P., BARNSLEY, M.J. & P.A. LONGLEY (eds.) (2001): *Remote Sensing and Urban Analysis*. Taylor & Francis Group, London & New York, 304 pp.

DOUGHERTY, M., DYMOND, R.L., GOETZ, S.J., JANTZ, C.A. & N. GOULET (2004): Evaluation of impervious surface estimates in a rapidly urbanizing watershed. In: *Photogrammetric Engineering and remote Sensing*, vol. 70, no. 11, pp. 1275-1284.

DOWN TO EARTH (2005): *Fact Sheet: Fresh Water Up for Grab*. Down to Earth, March 5. URL: http://www.downtoearth.org.in/node/123/2005-5-15 (access December 2014)

DUPONT, V. (2000): Spatial and demographic Growth of Delhi since 1947 and the Main Migration Flows. In: DUPONT, V., TARLO, E. & D. VIDAL (eds.): Delhi. Urban Space and Human Destinies, Manohar, Delhi, pp. 229-240.

EBERT, A., KERLE, N. & A. STEIN (2007): Remote sensing based assessment of social vulnerability. In: *Proc. of the 5th International Workshop on Remote Sensing Applications to Natural Hazards*, 110-11 September 2007, Washington, D.C., George Washington University, 7 pp.

EHLERS, E. & T. KRAFFT (eds.) (1998): *Shahjahanabad/Old Delhi. Tradition and Colonial Change*, Steiner Verlag, Stuttgart, 106 pp.

EHLERS, M. (2002): Fernerkundung für GIS-Anwender — Sensoren und Methoden zwischen Anspruch und Wirklichkeit. In: BLASCHKE, T. (eds.): *Fernerkundung und GIS – Neue Sensoren – innovative Methoden*, Wichmann Verlag, Heidelberg, pp. 10-23.

EHLERS, M. (2005): Urban Remote Sensing: New Developments and Trends. In: MOELLER, M. & E. WENTZ (eds.): *Proceedings of the ISPRS Joint Symposium URBAN 2005 and URS 2005*, 14-16 March 2005, Tempe, AZ, 6 pp.

EHLERS, M., SCHIEWE, J. & L. TUFTE (2005): Urban Remote Sensing: New developments and Challenges. In: MOELLER, M. & E. WENTZ (eds.): MOELLER, M. & E. WENTZ (eds.): *Proceedings of the ISPRS Joint Symposium URBAN 2005 and URS 2005*, 14-16 March 2005, Tempe, AZ, pp. 130-137.

EHLERS, M. (2007): Neue Sensoren in der Fernerkundung. In: *GIS-BUSINESS*, vol. 12, pp. 29-32.

ELVIDGE, C.D., SUTTON, P.C., TUTTLE, T., GHOSH, T. & K.E. BAUGH (2009): Global Mapping Based on Nighttime Lights. In: Gamba, P. & M. Herold (eds.) (2009): *Global Mapping of Human Settlements — Experiences, Datasets, and Prospects*. CRC Press, Taylor & Francis Group, Boca Raton, London, New York, 374 pp., ISBN: 978-1-4200-8339-2.

ESCH, T., ROTH, A., STRUNZ, G. & S. DECH (2003): Object-oriented classification of Landsat-7 data for regional planning purposes. In: *Proceedings of the ISPRS WG VII/4 Symposium Remote Sensing of Urban Areas*, 27-29 June 2003, Regensburg, Germany, pp. 50-55.

ESCH, T. & A. ROTH (2004): Semi-automated classification of urban areas by means of high resolution radar data. In: *Proceedings of ISPRS 2004 Congress*, 15-23 July 2004, Istanbul, Turkey, pp. 478-482.

ESCH, T., ROTH, A. & S. DECH (2005): Robust approach towards an automated detection of built-up areas from high resolution radar imagery. In: MOELLER, M. & E. WENTZ (eds.): *Proceedings of the ISPRS Joint Symposium URBAN 2005 and URS 2005*, 14-16 March 2005, Tempe, AZ, 6 pp.

ESCH, T., ROTH, A. & S. DECH (2006): Analysis of Urban Land Use Pattern Based on High Resolution Radar Imagery. In: Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, 2006, vol. 1, 31 July – 4 August 2006, Denver, CO, pp. 3615 – 3618.

ESCH, T., MARCONCINI, M., FELBIER, A., ROTH, A., HELDENS, W., HUBER, M., SCHWINGER, M., TAUBENBÖCK, H., MÜLLER, A. & S. DECH (2013): Urban footprint processor — Fully automated processing chain generating settlement masks from global data oft he TanDEM-X mission. In: *IEEE Geoscience & Remote Sensing Letters*, vol. 10, no. 6, pp. 1617-1621.

EVANS, C., JONES, R., SVALBE, I. & M. BERMAN (2002): Segmenting multispectral Landsat TM images into field units. In: *IEEE Transaction on Geoscience and Remote Sensing*, vol. 40, no. 5, pp. 1054-1064.

FALKENMARK, M. & C. WIDSTRAND (1992): Population and Water Resources: A Delicate Balance. In: *Population Bulletin*, Population Reference Bureau.

FAUST, K., ENTWISLE, B., RINDFUSS, R.R., WALSH, S.J. & Y. SAWANGDEE (1999): Spatial Arrangement of Social Economic Networks among Villages in Nang Rong District, Thailand. In: Social Networks, no. 21, pp. 311-337.

FAVEL, M., CHANUSSOT, J. & J.A. BENEDIKTSSON (2009): Kernel Principal Component Analysis for the Classification of Hyperspectral Remote Sensing Data over Urban Areas. In: *EURASIP Journal on Advances in Signal Processing,* vol. 2009, Article ID 783194, 14 pp. URL: http://www.hindawi.com/journals/asp/2009/783194.ref.html (access September 2009).

FELDBAUER; P. & C. PARNREITER (1997): Megastädte – Weltstädte – Global Cities. In: FELDBAUER, P., HUSA, K., PILZ, E. & I. STACHER (eds.): *Mega-Cities. Die Metropolen des Südens zwischen Globalisierung und Fragmentierung*. Historische Sozialkunde, vol. 12, pp. 9-19.

FOODY, G.M. (2002): Status of land cover classification accuracy assessment. In: *Remote Sensing of Environment*, vol. 80, pp. 185-201.

FORD, K. (ed.) (1979): *Remote Sensing for Planners*. Rutgers, State University of New Jersey, 219 pp.

FORSTER, B. (1983): Some urban measurements from Landsat data. In: *Photogrammetric Engineering and Remote Sensing*, vol. 49, pp. 1693-16707.

FORSTER, B.C. (1985): An examination of some problems and solutions in monitoring urban areas from satellite platforms. In: *International Journal of Remote Sensing*, vol. 6, pp. 139-151.

FORSTER, B.C. (1993): Coefficient of variation as a measure of urban spatial attributes using Spot HRV and Landsat TM data. In: *International Journal of Remote Sensing*, vol. 14, no. 12, pp. 2403-2409.

FORSYTHE, K.W. (2003): Monitoring "Megacity" Urban Development: Pansharpened Landsat 7 Results for Toronto, Ontario, Canada. In: The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (CD-ROM), vol. XXXIV-7/W9, Proceedings of the 4th International Symposium Remote Sensing of Urban Areas, Regensburg, Germany, 27-29 June 2003, pp. 60-65.

FRAUMAN, E. & E. WOLFF (2005): Segmentation of Very High Spatial Resolution Satellite Images in Urban Areas for Segments-Based Classification. In: MOELLER, M. & E. WENTZ (eds.): *Proceedings of the ISPRS Joint Symposium URBAN 2005 and URS 2005*, 14-16 March 2005, Tempe, AZ, 4 pp.

FREIXENET, J., MUÑOZ, X., RADA, D., MARTÍ, J. & X. CUFÍ (2002): Yet Another Survey on Image Segmentation: Region and Boundary Information Integration. In: HEYDEN, A. ET AL. (eds.) ECCV 2002, LNCS 2352, Springer-Verlag, Berlin, Heidelberg, pp. 408-422.

FU, K.S. & J.K. MUI (1981): A Survey on Image Segmentation. In: *Pattern Recognition*, vol. 13, pp. 3-16.

FUCHS, R. J., BRENNAN, E., CHAMIE, J., LO, F.-C. & J. I. UITTO (eds.) (1994): *Mega-city Growth and the Future*. United Nations University Press, Tokyo, New York, Paris, 428 pp.

FUKUNAGA, K. (1990): *Introduction to Statistical Pattern Recognition*. Academic Press Inc., New York, 2nd Edition, 592 pp.

GALLO, K.P., MCNAB, A.L., KARL, T.R., BROWN, J.F., HOOD, J.J. & J.D. TARPLEY (1993a): The use of vegetation index for assessment of the urban heat island effect. In: *International Journal of Remote Sensing*, vol. 14, no. 11, pp. 2223-2230.

GALLO, K.P., MCNAB, A.L., KARL, T.R., BROWN, J.F., HOOD, J.J. & J.D. TARPLEY (1993b): The use of NOAA AVHRR data for assessment of the urban heat island effect. In: *Journal of Applied Meteorology*, vol. 32, no. 5, pp. 899-908.

GALLO, K.P., TARPLEY, J.D., MCNAB, A.L. & T.R. KARL (1995): Assessment of urban heat islands: a satellite perspective. In: *Atmospheric Research*, vol. 37, no. 1-3, pp. 37-43.

GAMBA, P. & B. HOUSHMAND (2001): An efficient neural classification chain of SAR and optical urban images. In: *International Journal of Remote Sensing*, vol. 22, pp. 1535-1553.

GAMBA, P., DELL' ACQUA, F. & G. LISINI (2006): Change Detection of Multi-temporal SAR Data in Urban Areas Combining Feature Based and Pixel-based Techniques. In: *IEEE Transaction on Geoscience and Remote Sensing*, vol. 44, no. 10, pp. 2820-2827.

GAMBA, P., DELL'ACQUA, F. & L. ODASSO (2007a): Object-oriented building damage analysis in VHR optical satellite images of the 2004 Tsunami over Kalutara, Sri Lanka. In: *Proc. of Urban Remote Sensing Joint Event (URS)*, 11-13 April 2007, Paris, France, IEEE 07EX1577, ISBN 1-4244-0712-5/07.

GAMBA, P., DELL'ACQUA, F., TRIANNI, G. & M. STASOLLA (2007b): GIS and Remote Sensing for Disaster Assessment in Urban Areas. In: *Proc. of Urban Remote Sensing Joint Event (URS)*, 11-13 April 2007, Paris, France, 5 pp., IEEE 07EX1577, ISBN 1-4244-0712-5/07.

GAMBA, P. & F. DELL' ACQUA (2008): Fusion of Radar and Optical Data for Identification of Human Settlements. In: WENG, Q. (eds.): *Remote Sensing of Impervious Surfaces*. Taylor & Francis CRC Press, Boca Raton, 143-159 pp.

GAMBA, P. & M. HEROLD (eds.) (2009): *Global Mapping of Human Settlements: Experiences, Data Sets, and Prospects*. CRC Press, Taylor & Francis Group, Boca Raton, London, New York, 374 pp., ISBN: 978-1-4200-8339-2.

GAO, B., HUANG, Q., HE, C. & Q. MA (2015): Dynamics of Urbanization Levels in China from 1992 to 2012: Perspective from DMSP/OLS Nighttime Light Data. In: *Remote Sensing*, vol. 7, no. 2, pp. 1721-1735.

GEIß, C. & H. TAUBENBÖCK (2013): Remote sensing contributing to assess earthquake risk — from a literature review towards a road map. In: *Natural Hazards*, vol. 68, no. 1, pp. 7-48.

GEOGHEGAN, J., PRITCHARD JR., L., OGNEVA-HIMMELBERGER, Y., CHOWDHURY, R.R.,SANDERSON, S. & B.L. TURNER (1998): "Socializing the Pixel" and "Pixelizing the Social" in Land-Use and Land-Cover Change. IN: LIVERMAN, D., MORAN, E.F., RINDFUSS, R.R. & P.C. STERN (eds.): *People and Pixels. Linking Remote Sensing and Social Science*. National Academy Press, Washington, D.C., pp. 51-69.

GERRING, J. (2001): Social Science Methodology. A Critical Framework. Cambridge University Press, Cambridge, 324 pp.

GLUCH, R.M. (2002): Urban growth detection using texture analysis on merged Landsat TM and SPOT-P data. In: *Photogrammetric Engineering and Remote Sensing*, vol. 68, no. 12, pp. 1283-1288.

GLUCH, R., QUATTROCHI, D.A. & J.C. LUVALL (2006): A multi-scale approach to urban thermal analysis. In: WENG, Q. & D.A. QUATTROCHI (eds.): *Remote Sensing of Environment, vol. 104, Special Issue on Thermal Remote Sensing of Urban Areas*, pp. 123-132.

GOETZ, A.F.H., VANE, G., SOLOMON, J.E. & B.N: ROCK (1985): Imaging Spectrometry for Earth Remote Sensing. In: *Science*, vol. 4704, pp. 1147-1153.

GONG, P. & P.J. HOWARTH (1992): Frequency-based contextual classification and gray-level vector reduction for land use identification. In: *Photogrammetric Engineering and Remote Sensing*, vol. 58, pp. 67-73.

GONZALEZ, R.C. & R.E. WOODS (1993): *Digital Image Processing*. Addison-Weasley, Reading, MA, 716 pp.

GORTE, B. (1999): Supervised Segmentation by Region Merging. In: KANELLOPOULOS, I., WILKINSON, G.G. & T. MOONS (eds.): *Machine Vision and Advanced Image Processing in Remote Sensing*. Springer, Berlin, pp. 329-335.

GOUDIE, A.S. (2005): The Human Impact of the Natural Environment: Past, Present, Future. 6th Edition, Blackwell Publishing, Oxford, 376 pp.

GOVERNMENT OF INDIA & GOVERNMENT OF THE NATIONAL CAPITAL TERRITORY DELHI (GI & GNCT) (2001): *Urban Environmental and Infrastructure Improvement Project – Delhi 21*. Report. Delhi.

GREEN, N.E. (1957): Aerial photographic interpretation and social structure of the city. In: *Photogrammetric Engineering*, vol. 23, pp. 89-96.

GREIWE, A. & M. EHLERS (2004): Segment-based classification algorithm for multisensor image data. In: *Proceedings of SPIE Congrès Remote Sensing for Environmental Monitoring, GIS Applications, and Geology IV*, 14-16 September 2004, Maspalomas, Spain, pp. 32-42.

GREY, W.M.F., LUCKMAN, A.J. & D. HOLLAND (2003): Mapping Urban Change in the UK Using Satellite Radar Interferometry. In: *Remote Sensing of Environment*, vol. 87, no. 1, pp16-22.

GRÜBNER, O. (2011): A spatial epidemiological approach on well-being in urban slums – Evidence from Dhaka, Bangladesh. Doctoral Dissertation, Mathematisch-Naturwissenschaftliche Fakultät II, Humboldt-University Berlin, Germany, pp. 175.

GRUEN, A. (2008): Building Extraction from Aerial Imagery. In: WENG, Q. (ed.): *Remote Sensing of Impervious Surfaces*. Taylor & Francis CRC Press, Boca Raton, pp. 269-296.

GUINDON, B., ZHANG, Y. & C. DILLABAUGH (2004): Landsat urban mapping based on a combined spectral-spatial methodology. In: *Remote Sensing of Environment*, vol. 92, pp. 218-232.

GUPTA, N. (2006): Delhi nach der Teilung Indiens. Zur Flüchtlingsgeschichte einer Megastadt. In: AHUJA, R & C. BROSIUS (eds.): *Mumbai — Delhi — Kolkata. Annäherung an die Megastädte Indiens.* Draupadi Verlag, Heidelberg, 310 pp.

GUPTA, N. (2000): Chronology of Significant Events in Delhi. In: DUPONT, V., TARLO, E. & D. VIDAL (eds.): *Delhi. Urban Space and Human Destinies*, Manohar, Delhi, pp. 251.

GURNEY, C.M. & J.R.G. TOWNSHEND (1983): The use of contextual information in the classification of remotely sensed data. In: *Photogrammetric Engineering and Remote Sensing*, vol. 49, no. 1, pp. 55-64.

HAACK, B., GUPTILL, S., HOLZ, R., JAMPOLER, S., JENSEN, J. & R. WELCH (1997): Urban analysis and planning. In: *Manual of Photographic Interpretation*, American Society for Photogrammetry and Remote Sensing, Bethesda, MD, pp. 517-553.

HAFNER, J. & S.Q. KIDDER (1999): Urban heat island modelling in conjunction with satellite-derived surface/soil parameters. In: *Journal of Applied Meteorology*, vol 38, no. 4, pp. 448-465.

HAIDER, S. (2000): Migrant Women and Urban Experience in Squatter Settlement. In: DUPONT, V., TARLO, E. & D. VIDAL (eds.): Delhi Urban Space and Human Destinies. Manohar, Delhi, pp. 29-51.

HALL, G.B., MALCOLM, N.W. & J.M. PIWOWAR (2001): Integration of Remote Sensing and GIS to detect Pockets of Urban Poverty: The Case of Rosario, Argentina. In: *Transactions in GIS*, vol. 5, no. 3, pp. 235-253.

HALLE, W. (1999): Ausgewählte Algorithmen der Segmentierung und Klassifikation zur thematischen Bildverarbeitung in der Fernerkundung. *Forschungsbericht des Deutschen Zentrums für Luft- und Raumfahrt (DLR)*, vol. 99, no. 36, Cologne; Doctoral Dissertation, Technical University of Berlin, 113 pp.

HARALICK, R.M., SHANMUGAM, K. & H.I. DINSTEIN (1973): Texture Features for Image Classification. In: *IEEE Transactions on Systems, Man, and Cybernetics*, SMC, vol. 3, no.6, pp.610-621.

HARALICK, R.M. (1979): Statistical and Structural approaches to texture. In: *Proceedings of IEEE*, vol. 67, no. 5, pp. 786-804.

HARALICK, R.M. & L.G. SHAPIRO (1985): Image segmentation techniques. In: *Computer Vision, Graphics and Image Processing*, vol. 29, p. 100-132.

HARALICK, R.M. & L.G. SHAPIRO (1992): *Computer and Robot Vision*. Addison-Wesley, Reading, MA, 672 pp.

HARDOY, J.E., MITLIN, D. & D. SATTERTHWAITE (2001): Environmental Problems in an Urbanizing World. Finding Solutions for Cities in Africa, Asia and Latin America. Earthscan, London, 470 pp.

HARTVICH, F., KOSKINEN, K. & P. PELLIAKKA (2001): Change detection of urban areas using multitemporal Landsat TM satellite data in Turku, Finland. In: *Proceedings of Nordic GIS Conference*, 8-10 October 2001, Helsinki, Finland, 10 pp., URL: http://www.helsinki.fi/maantiede/geoinformatiikka/opetus/2005_2006/GISKeijo_Final.pdf (access August 2009).

HARVEY, J.T. (2002a): Estimating Census District Populations from Satellite Imagery: Some Approaches and Limitations. In: *International Journal of Remote Sensing*, vol. 23, no. 10, pp. 2071-95.

HARVEY, J.T. (2002b): Population Estimation Models Based on Individual TM Pixels. In: Photogrammetric Engineering and Remote Sensing, vol. 68, no. 11, pp. 1181-92.

HARVEY, J.T. (2003): Population estimation at the pixel level: developing the expectation maximization technique. In: MESEV, V. (ed.) (2003): *Remotely Sensed Cities*. Taylor & Francis, London, New York, pp. 181-206.

HAVERKAMP, D. (2002): Extracting straight road structure in urban environments using IKONOS satellite imagery. In: *Optical Engineering*, vol. 41, no. 9, pp. 2107-2110.

HAY, G. & G. CASTILLA (2006): Object-Based Image Analysis: Strengths, Weaknesses, Opportunities and Threats (SWOT). In: The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI-4/C42, 3 pp.

HEIDEN, U., ROESSNER, S., SEGL, K. & H. KAUFMANN (2001): Analysis of Spectral Signatures of Urban Surfaces for their Area-wide Identification Using Hyperspectral HyMap data. In: *Proceedings of the IEEE/ISPRS Joint Workshop on Remote Sensing and Data Fusion in Urban Areas*, Rome, Italy, pp. 173-177.

HEIDEN, U., HELDENS, W., ROESSNER, S., SEGL, K., ESCH, T. & A. MÜLLER (2012): Urban structure type characterization using hyperspectral remote sensing and height information. In: *Landscape and Urban Planning*, vol. 105, no. 4, pp. 361-375.

HEINRICHS, D. (2010): Problemfall Megacitys. Hürden der Urbanisierung. In: The European. URL: http://theeuropean.de/dirk-heinrichs/4378-problemfall-megacities (access November 2014).

HEINRICHS, D. & S. KABISCH (2006): Risikolebensraum Megacity. Strategien für eine nachhaltige Entwicklung in Megastädten und Ballungszentren. In: *Mitteilungen der HGF*, GAiA 15/2, pp. 157-161.

HENDERSON, F.M. & Z.-G. XIA (1997): SAR Applications in Human Settlement Detection, Population Estimation and Urban Land Use Pattern Analysis: A Status Report. In: *IEEE Transactions on Geoscience and Remote Sensing*, vol. 35, no. 1, pp. 79-85.

HEPNER, G.F. & J. CHEN (2001): Investigation of Imaging Spectroscopy for Discriminating Urban Land Covers and Surface Materials. In: *Proc. of the AVIRIS Earth Science and Applications Workshop*, Palo Alto, CA, 3 pp. URL: ftp://popo.jpl.nasa.gov/pub/docs/workshops/01_docs/2001Chen_web.pdf (access November 2014).

HEROLD, M., MENZ, K. & K. CLARKE (2001): Remote sensing and urban growth models — demands and perspectives. In: JÜRGENS, C. (ed.): *Proceedings of the Symposium on Remote Sensing of Urban Areas*, 22-23 June 2001, Regensburger Geographische Schriften 35, Regensburg, Germany, CD-ROM.

HEROLD, M., GOLDSTEIN, N.C. & K.C. CLARKE (2003): The spatiotemporal form of urban growth: Measurement, analysis and modelling. In: *Remote Sensing of Environment*, vol. 86, pp. 286-302.

HEROLD, M. (2004): Remote Sensing and Spatial Metrics for Mapping and Modeling of Urban Structures and Growth Dynamics. Doctoral Dissertation, University of California, Santa Barbara, 325 pp.

HEROLD, M., HEMPHILL, J., DIETZEL, C. & K.C. CLARKE (2005): Remote Sensing Derived Mapping to Support Urban Growth Theory. In: MOELLER, M. & E. WENTZ (eds.): *Proceedings of the ISPRS Joint Symposium URBAN 2005 and URS 2005*, 14-16 March 2005, Tempe, AZ, 6 pp.

HEROLD, M. & C.C. SCHMULLIUS (2005): International Earth Observation Initiatives and Programs: The Context for Global Urban Mapping. In: MOELLER, M. & E. WENTZ (eds.): *Proceedings of the ISPRS Joint Symposium URBAN 2005 and URS 2005*, 14-16 March 2005, Tempe, AZ, 6 pp.

HEROLD, M., HEMPHILL, J., LIU, X. & K.C. CLARKE (2006): Urban Patterns and Processes: A Remote Sensing perspective. In: *Proc. 1st EARSeL Workshop of the SIG Urban Remote Sensing*, 02-03 March 2006, Berlin, 4 pp.

HEROLD, M. (2008): Spectral Characteristics of Asphalt Road Surfaces. In: WENG, Q. (ed.): *Remote Sensing of Impervious Surfaces*. Taylor & Francis CRC Press, Boca Raton, pp. 237-250.

HESE, S. & C. SCHMULLIUS (2005): Forest Cover Change in Siberia — Results from the Siberia-II Project. In: *Proc. of the International Symposium on remote Sensing of Environment (ISRSE)*, 20-24 June 2005, St. Petersburg, Russia, 4 pp.

HILDEBRANDT, G. (1996): Fernerkundung und Luftbildmessung für Forstwirtschaft, Vegetationskartierung und Landschaftsökologie. Herbert Wichmannn Verlag, Heidelberg, 1st ed., 680 pp.

HOFFHINE WILSON, E., HURD, J.D., CIVCO, D. L., PRISLOE, M.P. & C. ARNOLD (2003): Development of a geospatial model to quantify, describe and map urban growth. In: *Remote Sensing of Environment,* vol. 86, pp. 275-285.

HOFMANN, P. (2001a): Detecting Informal Settlements from IKONOS Image Data Using Methods of Object Oriented Image Analysis — An Example from Cape Town (South Africa).In: *2nd International Symposium Remote Sensing of Urban Areas*, 22-23 June 2001, Regensburg, Germany, pp. 107-118.

HOFMANN, P. (2001b): Detecting urban features from IKONOS data using an object oriented approach. In: *Proceedings of the 1st Annual Conference Remote Sensing and Remote Sensing Society*, pp. 28-33.

HOFMANN, P., STROBL, J., BLASCHKE, T. & H. KUX (2006): Detecting Informal settlements from QickBird data in Rio de Janeiro Using an Object Based Approach. In: *Proc. 1st Int. Conf. on Object-Based Image Analysis (OBIA)*, 4-5 July 2006, Salzburg, Austria, 6 pp.

HOFMANN, P., STROBL, J. & T. BLASCHKE (2008): A Method for Adapting Global Image Segmentation Methods to Images of Different Resolutions. In: *Proceedings of the GEOBIA 2008 — Pixels, Objects, Intelligence. GEOgraphic Object Based Image Analysis for the 21st Century*, 5-8 August 2008, University of Calgary, Calgary, Alberta, Canada, ISPRS vol. no. XXXVIII, part 4/C1, ISSN no.1682-1777, 7 pp. URL:

http://homepages.ucalgary.ca/~gjhay/geobia/Proceedings/Sessions/Session5/6786_Hofmann_Proc_pap.pdf (access November 2014).

HOFSTEE, P. & M. ISLAM (2004): Disaggregation of Census Districts: Better Population Information for Urban Risk Management. In: *Proc. of 25th ACRS 2004*, Chiang Mai, Thailand, pp. 1206-1211.

HOSTERT, P. (2007): Advances in Urban Remote Sensing: Examples from Berlin (Germany). In: NETZBAND, M., STEFANOV, W.L. & C. REDMANN (EDS): *Applied Remote Sensing for Urban Planning, Governance and Sustainability*. Springer Verlag, Berlin, pp. 37-51.

HOSTERT, P. (2010): Processing techniques for hyperspectral data. In RASHED, T. & C. JÜRGENS (eds.): *Remote Sensing of Urban and Suburban Areas*, Springer, Dordrecht, Heidelberg, London, New York, 352 pp.

HUDSON, W.D. & W. RAMM (1987): Correct Formulation of the Kappa Coefficient of Agreement. In: *Photogrammetric Engineering and Remote Sensing*, vol. 53, no. 4, pp. 421-422.

HURSKAINEN, P. & P. PELIKKA (2004): Change Detection of Informal Settlements Using Multi-Temporal Aerial Photographs — The Case of Voi, SE-Kenya. In: *Proceedings of the 5th AARSE conference*: *Geoinformation sciences in support of Africa´s development*, 18-21 October 2004, Nairobi, Kenya, 9 pp.

IEEE (2007): *Megacities. A How-To Manual for the Megacity – an IEEE Spectrum Special Report*. URL: http://spectrum.ieee.org/static/moremegacity (access November 2014).

JAIN, A.K. (1990): *The Making of a Metropolis. Planning and Growth of Delhi.* National Book Organisation, New Delhi, 283 pp.

JAIN, S., SOKHI, B.S., U. SUR (2005): Slum Identification Using High-resolution Satellite Data. In: *GIM International*, vol. 19, no. 9, pp. 60-63.

JANSSEN, L.L.F. & F.J.M. VAN DER WEL (1994): Accuracy Assessment of Satellite Derived Land-Cover Data: A Review. In: *Photogrammetric Engineering & Remote Sensing*, vol. 60, no. 4, pp. 419-426.

JENSEN, J.R. (1983): Urban/suburban land use analysis. In: Manual of Remote Sensing, 2nd Edition ASP, Falls Church, pp. 1571-1666.

JENSEN, J.R. (1996): *Introductory digital image processing: a remote sensing perspective*. Prentice Hall Series in Geographic Information Science, 316 pp.

JENSEN, J.R. & D.C. COWEN (1999): Remote Sensing of Urban/Suburban Infrastructure and Socio-Economic Attributes: In: *Photogrammetric Engineering & Remote Sensing*, vol. 65, no. 5, pp. 611-622.

JENSEN, J.R. (2006): *Remote Sensing of the Environment. An Earth Resource Perspective*. Prentice Hall, 2nd edition, New Jersey, 608 pp.

JI, M. & J.R. JENSEN (1999): Effectiveness of subpixel analysis in detecting and quantifying urban imperviousness from Landsat Thematic mapping imagery. In: *Geocarto International*, vol. 14, no. 4, pp. 33-41.

JI, Z., CHEN, Y.H., JING, L., WENG, Q.H. & T. YAN (2007): Estimation and seasonal monitoring of urban vegetation abundance based on remote sensing. In: *Proceedings of SPIE, Geoinformatics 2007: Remotely Sensed Data and Information*, 25-27 May 2007, Nanjing, China, vol. 6752, no. 2, xx pp.

JOHNSTON, R. J., TAYLOR, P. J. & M. J. WATTS (eds.) (2002): *Geographies of Global Change. Remapping the World*. 2nd Edition, Blackwell Publishing, Oxford, 544 pp.

JUNG, A., TÖKEI, L. & P. KARDEVÁN (2007): Application of airborne hyperspectral and thermal images to analyse urban microclimate. In: *Applied Ecology and Environmental Research* vol. 5, no. 1, pp. 165-175.

KAMPOURAKI, M., WOOD, G.A. & T. BREWER (2006): The Application of Remote Sensing to Identify and Measure Sealed Areas in Urban Environments. In: *Proc. 1st Int. Conf. on Object-Based Image Analysis (OBIA)*, 4-5 July 2006, Salzburg, Austria, 5 pp.

KANJIR, U., VELJANOVSKI, T. & P. KOVAČIČ (2012): Using VHR Satellite Imagery to Estimate Populations in Informal Settlements. In: *Proceedings of the 4th GEOBIA*, 7-9 May, Rio de Janeiro, Brazil, pp. 566-571.

KEINER, M. & W.A. SCHMID (2003): Urbanisierungstendenzen in Entwicklungsländern. Probleme und Potentiale für nachhaltige Stadtentwicklung. In: *DISP*, vol. 155, no. 4, pp. 49-56.

KETTIG, R.L. & D.A. LANDGREBE (1976): Classification of Multispectral Image Data by Extraction and Classification of Homogeneous Objects. In: *IEEE Transactions on Geoscience Electronics*, vol. GE-14, no. 1, p. 19-26.

KIM, H.H. (1992): Urban heat island. In: *International Journal of Remote Sensing*, vol. 13, no. 12, pp. 2319-2336.

KIM, H.-O., KENNEWEG, H. & B. KLEINSCHMIT (2006): A New Approach Towards Mapping Urban Sealing Using the Very High-Resolution Satellite Data in Seoul Metropolitan Areas. In: *Proceeding of 1st Workshop of the EARSeL-SIG Urban Remote Sensing "Urban Remote Sensing, Challenges and Solutions"*, 2-3 March 2006, Berlin, Germany, 7 pp.

KIT, O. & M. LÜDEKE (2013): Automated detection of slum area change in Hyderabad, Idia using multitemporal satellite imagery. In: *ISPRS Journal of Photogrammetra and Remote Sensing*, vol. 83, pp. 130-137, DOI: 10.1016/j.isprsjprs.2013.06009.

KLEINSCHMIT, B., FÖRSTER, M., FRICK, A. & K. OEHMCHEN (2007): QuickBird Data – experiences with ordering, quality and pan sharpening. PFG - Photogrammetrie, Fernerkundung, Geoinformation, vol. 2, pp. 73-83.

KÖBERLEIN, M. (2003): Living from Waste. Livelihoods of the Actors Involved in Delhi's Informal Waste Recycling Economy. In: Studien zur Geographischen Entwicklungsforschung 24. Verlag für Entwicklungspolitik, Saarbrücken, Germany.

KOHLI, D., WARWADEKAR, P., KERLE, N., SLIUZAS, R. & A. STEIN (2013): Transferability of object-oriented image analysis methods for slum identification. In: *Remote Sensing*, vol. 5, pp. 4209-4228.

KOLEHMAINEN, K. & Y. BAN (2008): Multitemporal SPOT Images for Urban Land-Cover Change Detection over Stockholm between 1986 and 2004. In: *Proceedings of ISPRS congress "Remote Sensing and Spatial Information Sciences*, vol. XXXVII, part B6b, 2008, Beijing, China, 4 pp., URL: http://www.isprs.org/congresses/beijing2008/proceedings/6b_pdf/11.pdf (access August 2009).

KÖTTER, T. (2004): Risk and Opportunities of Urbanization and Megacities. *Proceedings of the FIG Working Week: The Olympic Spirit of Surveying*, edited by FIG (Athens), 9 pp.

KRAAS, F. (2003): Megacities as Global Risk Areas. *Petermanns Geographische Mitteilungen*, vol. 147, no. 4, pp. 6-15.

KRAAS, F. (2005): Megacities: Urban Dynamics of Global Change. In: KRAFFT, T. & W. MAUSER (eds.): *Global Change Research in Germany*, German National Committee of Global Change Research (NKGCF), Munich, pp. 21-22.

KRAAS, F. (2006): Urbanization, mega-cities and disaster reduction. In: TETZLAFF, G., ZENTEL, K.-O. & P. ZARIAN (eds.): *Common Problems, Common Solutions: Linking the Scientific and Disaster Risk reduction Communities*. 2nd International Symposium on Disaster Reduction and Global Environmental Change. German Committee for Disaster Reduction - DKKV, 19-20 December 2005, Bonn, Germany, pp. 34-37.

KRAAS, F. (2007a): Megastädte. In: GEBHARDT, H., GLASER, R., RADTKE, U. & P. REUBER (eds.): *Geographie. Physische Geographie und Humangeographie*, vol. 1, Spektrum Verlag, Heidelberg, pp. 876-880.

KRAAS, F. (2007b): Megacities and Global Change in East, Southeast and South Asia. *Asien*, vol. 103, pp. 9-22.

KRAAS, F. (2007c): Megacities and global change: key priorities. *Geographical Journal*, vol. 173, no. 1, pp. 79-82.

KRAAS, F., MAUSER, W., KRAFFT, T., LÖW, A., NIEBERGALL, S., SELBACH, V. & R. SINGH (2007d): *Vulnerability in Megacities: New Approaches to Analyse the Urban Water System in Delhi, India*. Risk Analysis Using an Integrated Approach: High-Resolution Remote Sensing, GIS and Qualitative/Quantitative Social Data, status report, May 2007, 88 pp.

KRAAS, F. & U. NITSCHKE (2006): Megastädte als Motoren des globalen Wandels. Neue Herausforderungen weltweiter Urbanisierung. *Internationale Politik*, vol. 61, no. 11, pp. 18-28.

KRAFFT, T. (1996): Delhi. In: *Geographische Rundschau*, vol. 48, no. 2, pp. 104-112.

KRAFFT, T. (2001): Delhi. In: BECKEL, L. (ed.): *Megacities*, Geospace, Salzburg, pp. 120-126.

KRAFFT, T., WOLF, T. & S. AGGARWAL (2003): A New Urban Penalty? Environmental and Health Risks in Delhi. In: *Petermanns Geographische Mitteilungen*, vol. 147, no. 4, pp. 20-27.

KRÖHNERT, S. (2003): Megastädte. Berlin-Institut für Weltbevölkerung und globale Entwicklung, 5 pp. URL: http://berlin-institut.org/pages/buehne/buehne_urbanisierung_ kroehnert_megastdt.html# (access June 2008).

KUFFER, M., K. PFEFFER, BAUD, I.S.A. & R. SLIUZAS (2013): Analysing Sub-Standard Areas Using High Resolution Remote (VHR) Sensing Imagery. Case Study of Mumbai, India. In: *Proceedings of the N-AERUS XIV Conference*, 12-14 September 2013, Enschede, 16 pp.

KUX, H.J. & C.M. DUQUE DE PINHO (2006): Object-Oriented Analysis of High-resolution Satellite Images for Intra-Urban Land Cover Classification: Case Study in São Paulo State, Brazil. In: *Proc. 1st Int. Conf. on Object-Based Image Analysis (OBIA)*, 4-5 July 2006, Salzburg, Austria, 6 pp., vol. no. XXXVI-4/C42, ISSN 1682-1777.

LANG, S. & T. BLASCHKE (2006): BRIDGING REMOTE SENSING AND GIS — WHAT ARE THE MAIN SUPPORTIVE PILLARS? IN: *Proceedings of the 1st International Conference on Object-based Image Analysis (OBIA 2006)*, 4-5 July 2006, Salzburg, Austria, 6 pp.

LALIBERTE, A.S., RANGO, A., HAVSTAD, K.M., PARIS, J.F., BECK, R.F., MCNEELY, R. & A.L. GOMEZ (2004): Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. In: *Remote Sensing of Environment*, vol. 93, no. 1-2, pp. 198-210.

LEMMA, T., SLIUZAS, R. & M. KUFFER (2006): A Participatory Approach to Monitoring Slum Conditions: an Example from Ethiopia. In: *Participatory Learning & Action*, vol. 54, pp. 54-58.

LETOURNEL, V., SANKUR,B., PRADEILLES, F. & F. MAITRE (2002): Feature Extraction for Quality Assessment of Aerial Image Segmentation. In: *ISPRS Technical Commission III Symposium*, Graz, Austria, 6 p.

LEVINE, M. & A. NAZIF (1985): Dynamic Measurement of Computer Generated Image Segmentation. In: *IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 7, no. 2, pp. 155-164.

LI, B. & H. RÜTHER (1999): IS-Modeler: A Low-Cost Image-Based Tool for Informal Settlement Planning. In: *Geoinformatics and Socioinformatics. The Proceedings of Geoinformatics ´99 Conference*, 19-21 June 1999, Ann Arbor, pp. 1-9.

LI, P., XU, H. & S. LI (2010): Urban Impervious Surface Extraction from Very High Resolution Imagery by One-Class Support Vector Machine. In: WAGNER, W. & B. SZÉKELY (eds.): *ISPRS TC VII Symposium – 100 Years ISPRS*, 5-7 July, Vienna, Austria, IAPRS, vol. XXXVIII, Part 7B, 5 pp.

LI, C., YIN, J. & J. ZHAO (2010B): Extraction of urban vegetation from high resolution remote sensing image. In: *Proceedings of the 2010 International Conference Computer Design and Applications (ICCDA)*, vol. 5, 25-27 June, Qinhuangdao, China, pp. 4-403 – 4-406.

LIANG, B., WENG, Q. & D. LU (2008): Using Remotely Sensed Impervious Surface Data to Estimate Population. In: WENG, Q. (ed.): *Remote Sensing of Impervious Surfaces*. Taylor & Francis CRC Press, Boca Raton, pp. 409-430.

LIU, X. & K. CLARKE (2002): Estimation of Residential Population Using High Resolution Satellite Imagery. In: *Proc. 3rd International Symposium on Remote Sensing of Urban Areas*, 11-13 June 2002, Istanbul, Turkey, pp. 153-160.

LIU, X. & M. HEROLD (2007): Population Estimation and Interpolation Using Remote Sensing. In: WENG, Q. & D.A. QUATTROCHI (eds.): *Urban Remote Sensing*. Taylor & Francis, New York, pp. 269-290.

LILLESAND, T.M., KIEFER, R.W. & J.W. CHIPMAN (2004): *Remote Sensing and Image Interpretation*, John Wiley & Sons, 5th ed., New York, 763 pp.

LIVERMAN, D., MORAN, E.F., RINDFUSS, R.R. & P.C. STERN (1998) (eds.): *People and Pixels. Linking Remote Sensing and Social Science*. National Academy Press, Washington, D.C., 256 pp.

LO, C.P. (1995): Automated Population and Dwelling Unit Estimation from High-Resolution Satellite Images: A GIS Approach. In: *International Journal of Remote Sensing*, vol. 16, no. 1, pp. 17-34.

LO, C.P. & B.J. FABER (1997): Integration of Landsat Thematic Mapper and Census Data for Quality of Life Assessment. In: *Remote Sensing of Environment*, vol. 62, pp. 143-157.

LO, C.P., QUATTROCHI, D.A. & J.C. LUVALL (1997): Application of high-resolution thermal infrared remote sensing and GIS to assess the urban heat island effect. In: *International Journal of Remote Sensing*, vol. 18, pp. 287-304.

LO, C.P. & D.A. QUATTROCHI (2003): Land-use and land-cover change, urban heat island phenomenon, and health implications: A remote sensing approach. In: *Photogrammetric Engineering and Remote Sensing*, vol. 69, no. 9, pp. 1053-1063.

LU, D. & Q. WENG (2008): Mapping Urban Impervious Surfaces from Medium and High Spatial Resolution Multispectral Imagery. In: WENG, Q. (eds.): *Remote Sensing of Impervious Surfaces*. Taylor & Francis CRC Press, Boca Raton, 59-73 pp.

LULLA, V. (2009): Hyperspectral Applications in Urban Geography. In: GATRELL, J.D. & R.R. JENSEN (eds.): *Planning and Socioeconomic Applications*. Springer Netherlands, pp. 79-86.

MAKELA, H. & A. PEKKARINEN (2001): Estimation of timber volume at the sample plot level by means of image segmentation and Landsat TM imagery. In: *Remote Sensing of Environment*, vol. 77, no. 1, pp. 66-75.

MALLET, C., SOERGEL, U. & F. BRETAR (2008): Analysis of Full-Waveform LIDAR Data for Classification of Urban Areas. In: *Proceedings of ISPRS congress "Remote Sensing and Spatial Information Sciences*, vol. XXXVII, part B6b, 2008, Beijing, China, 8 pp., URL: http://www.isprs.org/congresses/beijing2008/proceedings/6b_pdf/11.pdf (access August 2009).

MALING, D.H. (1989): *Measurements from maps* – principles and methods of cartometry. Pergamon Press, Oxford, 577 pp.

MANN, M. (2006): Metamorphosen einer Metropole: Delhi 1911-1977. In: AHUJA, R & C. BROSIUS (eds.): *Mumbai — Delhi — Kolkata. Annäherung an die Megastädte Indiens.* Draupadi Verlag, Heidelberg, 310 pp.

MARANGOZ, A.M., ORUC, M. & G. BUYUKSALIH (2004): Object-oriented image analysis and semantic network for extracting the roads and buildings from IKONOS pan-sharpened images. In: *Proceedings of the ISPRS 2004 Annual Conference*, 19 - 23 July 2004, Istanbul, Turkey, 4 pp.

MARCHESI, A., COLOMBO, R. & P. VALENTINI (2006): Application of High Spatial Resolution Satellite Imagery for Urban Environment Mapping. In: *Proc. 1st Int. Conf. on Object-Based Image Analysis (OBIA)*, 4-5 July 2006, Salzburg, Austria, pp. 4-5, vol. no. XXXVI-4/C42, ISSN 1682-1777.

MARPU, P.R., NIEMEYER, I. & R. GLOAGUEN (2006): A Procedure for Automatic Object-Based Classification. In: *PROCEEDINGS OF THE 1ST INTERNATIONAL CONFERENCE ON OBJECT-BASED IMAGE ANALYSIS (OBIA 2006)*, 4-5 JULY 2006, SALZBURG, AUSTRIA, 5 PP.

MARTIN, D.J. & I. BRACKEN (1993): The integration of socioeconomic and physical resource data for applied land management information systems. In: *Applied Geography*, vol. 13, pp. 45-53.

MASHEE, H.A. (2009): Object-oriented Image Analysis for Monitoring Urban Expansion in the City of Riyadh, Saudi Arabia. Unpublished Msc Dissertation at the University of Edinburgh.

MASSER, I. (2001): Managing our urban future: The role of remote sensing and geographic information systems. In: *Habitat International*, vol. 25, pp. 503-512.

MASON, S. & E. BALTSAVIAS (1997): Image-Based Reconstruction of Informal Settlements. In: *Proceedings of 17th International Workshop "Automatic Extraction of Man-Made Objects from Aerial and Space Images (II)"*, 5-9 May 1997, Ascona, Switzerland, 12 pp., URL: http://e-collection.ethbib.ethz.ch/view/eth:25206 (access August 2009).

MASEK, J.G., LINDSAY, F.E. & S.N. GOWARD (2000): Dynamics of urban growth in the Washington DC metropolitan area, 1973-1996, from Landsat observations. In: *International Journal of Remote Sensing*, vol. 21, pp. 3473-3486.

MASON, S. & E.P. BALTSAVIAS (1997): Image-based reconstruction of Informal Settlements. In: Grün, A., Baltsavias, E. & O. Henricsson (eds.): *Automatic Extraction of Man-Made Objects from Aerial and Space Images* (II), Birkhäuser Verlag, Basel, pp. 97-108.

MASON, S.O. & C.S. FRASER (1998): Image Sources for Informal Settlement Management. In: *The Photogrammetric Record*, vol. 16, no. 92, pp. 313-330.

MATHER, P.M. (1999): Land Cover Classification Revisited. In: ATKINSON, P.M. & N.J. TATE (eds.): *Advances in Remote Sensing and GIS*. John Wiley & Sons, New York, pp. 7-16.

MATHER, P.M. (2004): Computer Processing of Remotely-Sensed Images. An Introduction. 3rd ed., John Wiley & Sons, 324 pp.

MATINFAR, H.R., SARMADIAN, F., ALAVI PANAH, S.K. & R.J. HECK (2007): Comparisons of Object-Oriented and Pixel-Based Classification of Land Use/Land Cover Types Based on Landsat 7, ETM+ Spectral Bands (Case Study: Arid Region of Iran). In: *American-Eurasian Journal Agric. & Environ. Sciences*, vol. 2, no. 4, pp. 448-456.

MAUSER, W., KRAAS, F., KRAFFT, T., LÖW, A., NIEBERGALL, S., SELBACH, V. & R. SINGH (2006): Vulnerability in megacities: An integrated approach using high resolution satellite data and social science analysis. In: WUYI, W., KRAFFT, T. & F. KRAAS (eds.): *Global Change, Urbanisation and Health*, China Meteorological Press, Beijing, China, pp.225-239.

MAVRANTZA, O.D. & D.P. ARGIALAS (2006): Object-Oriented Image Analysis for the Identification of Geologic Lineaments. In: *Proc. 1st Int. Conf. on Object-Based Image Analysis (OBIA)*, 4-5 July 2006, Salzburg, Austria, 6 pp.

MC LAREN, R., COLEMAN, D. & S. MAYUNGA (2005): Sustainable Management of Mega Growth in Megacities. In: Proc. of the FIG Working Week: From Pharaos to Geoinformatics, 15 pp.

MEAILLE, R. & L. WALD (1990): Using geographical information system and satellite imagery within a numerical simulation of regional growth. In: *International Journal of Geographical Information Systems,* vol. 4, no. 4, p. 445-456.

MEHRA, A.K. (2005): Urban Villages of Delhi. In: HURST, E. & M. MANN (eds.): *Urbanization and Governance in India*, Manohar, Delhi, pp. 279-310.

MEINEL, G., NEUBERT, M. & J. REDER (2001): The Potential Use of Very High Resolution Satellite Data for Urban Areas — First Experiences with Ikonos Data, their Classification and Application in Urban Planning and Environmental Monitoring. In: JÜRGENS, C. (ed): *Proceedings of 2nd Symposium Remote Sensing of Urban Areas*, 22 - 23 June 2001, Regensburg, Germany, Regensburger Geographische Schriften, no. 35, pp. 196-205.

MEINEL, G., NEUBERT, M. & J. REDER (2002): Pixelorientierte versus segmentorientierte Klassifikation von IKONOS-Satellitendaten. In: Photogrametrie-Fernerkundung-Geoinformation (PFG), vol. 3, pp. 157-170.

MEINEL, G. & M. NEUBERT (2004): A Comparison of Segmentation Programs for High Resolution Remote Sensing Data. In: *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXV-B4, pp. 1097-1102.

MELESSE, A.M., WENG, Q., THENKABAIL, P.S. & G.B. SENAY (2007): Remote Sensing Sensor and Applications in Environmental Resources Mapping and Modelling. In: *Sensors 2007*, vol. 7, pp. 3209-3241.

MELESSE, A.M. & X. WANG (2008): Impervious Surface Area Dynamics and Storm Runoff Response. In: WENG, Q. (ed.): *Remote Sensing of Impervious Surfaces*. Taylor & Francis CRC Press, Boca Raton, pp. 369-386.

MENON, A.G.K. (2000): The Contemporary Architecture of Delhi: The Role of the State as Middleman. In: DUPONT, V., TARLO, E. & D. VIDAL (eds.): *Delhi. Urban Space and Human Destinies*, Manohar, Delhi, pp. 143-157.

MERTES, C.M., SCHNEIDER, A., SUALL-MENASHE, D., TATEM, A.J. & B. TAN (2015): Detecting change in urban areas at continental scales with MODIS data. In: *Remote Sensing of Environment*, vol. 158, pp. 331-347.

MERTINS, G. (1992): Urbanisierung, Metropolisierung und Megastädte. Ursachen der Stadtexplosion in der Dritten Welt. In: Deutsche Gesellschaft für die Vereinten Nationen (eds.): *Mega-Städte — Zeitbombe mit globalen Folgen?* Dokumentationen, Informationen, Bonn, pp. 7-21.

MESEV, V. (ed.) (2003): *Remotely Sensed Cities*. Taylor & Francis, London, New York, 365 pp.

METROPOLIS, N. & S. ULAM (1949): The Monte Carlo Method. In: *Journal of the American Statistical Association*, vol. 44, no. 247, pp. 335-341.

MEIER KRUKER, V. & J. RAUH (2005): Arbeitsmethoden der Humangeographie. WBG (Wissenschaftliche Buchgesellschaft), 182 pp.

MEZARIS, V., KOMPATSIARIS, I. & M.G. STRINTZIS (2004): Still Image Segmentation Tools for Object-based Multimedia Applications. In: *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 18, no. 4, pp. 701-725.

MILLER, R.B. & C. SMALL (2003): Cities from space: potential applications of remote sensing in urban environmental research and policy. In: *Environmental Science and Policy*, vol. 6, pp. 129-137.

MISTELBACHER, J. (2005): Urbanisierungsdynamik in Indien. Das Beispiel Delhi. In: *Geographische Rundschau*, vol. 57, no. 10, pp. 20-29.

MITCHELL, J. K. (1999a): Megacities and natural disasters: a comparative analysis. *GeoJournal*, vol. 49, no. 2, pp. 137-142.

MITCHELL, J. K. (1999b): *Crucibles of Hazard: Mega-cities and Disasters in Transition*. United Nations University Press, Tokyo and New York.

MODI, P.N. (1998): *Water Supply Engineering*. Standard Book House, Delhi.

MOELLER, M.S., STEFANOV, W.L. & M. NETZBAND (2004): Characterizing Landcover Changes in a Rapidly Growing Metropolitan Area Using Long Term Satellite Imagery. In: *Proceedings of ASPRS Annual Conference*, May 2004, Denver, Colorado, 9 pp.

MOELLER, M.S. (2005): Remote Sensing for the Monitoring of Urban Growth Patterns. In: MOELLER, M. & E. WENTZ (eds.): *Proceedings of the ISPRS Joint Symposium URBAN 2005 and URS 2005*, 14-16 March 2005, Tempe, AZ, 6 pp.

MØLLER-JENSEN, L. & P. YANKSON (1994): Assessing the Land Cover Change of Accra Using Landsat-TM Data. In: *Geografisk Tidsskrift – Danisch Journal of Geography*, vol. 94, no. 1, pp. 21-25, DOI: 10.1080/00167223.1994.10649348.

MONIER, R.B. & N.E. GREEN (1953): Preliminary findings on the development of criteria for the identification of urban structures from aerial photographs. In: *Annals of the Association of American Geographers*, special issue.

MOORE, M., GOULD, P. & B.S. KEARY (2003): Global urbanization and impact on health. *International Journal of Hygiene and Environmental Health*, vol. 206, pp. 269-278.

MOREL, J.-M. & S. SOLIMINI (1995): *Variational methods for image segmentation*. Birkhäuser, Boston, 245 pp.

MÜCK, M., TAUBENBÖCK, H., POST, J., WEGSCHEIDER, S., STRUNZ, G. & I.F.A. SUMARYONO (2013): Assessing building vulnerability to earthquake and tsunami hazard using remotely sensed data. In: *Natural Hazards*, vol. 68, no. 1, pp. 97-114.

MUMFORD, L. (1961): The City in History: It´s Origins, It´s Transformations, and the Prospects. Hartcourt, Brace & World, New York, 657 pp.

MYNENI, R.B., HALL, F.G., SELLERS, P.J. & A.L. MARSHAK (1995): The interpretation of spectral vegetation indexes. In: *IEEE Transaction on Geoscience and Remote Sensing*, vol. 33, no. 2, pp.481-486.

NAVULUR, K. (2007): *Multispectral Image Analysis Using the Object-Oriented Paradigm*. CRC Press, Taylor & Francis Group, Boca Raton, London, New York, 165 pp.

NEGRI, M., GAMBA, P., LISINI, G. & F. TUPIN (2006): Junction-Aware Extraction and Regularization of Urban Road networks in High-Resolution SAR Images. In: *IEEE Transactions on Geoscience and Remote Sensing*, vol. 44, no. 10, pp. 2962-2971.

NETZBAND, M., WENTZ, E.L. & A. RAHMAN (2005): Urban Land Cover and Spatial Variation Observation Using Satellite Image Data — The Urban Environmental Monitoring Project. In: Proceedings of XXVIIIth URSI General Assembly, 23-29 October 2005, New Delhi, India, 4 pp.

NETZBAND, M., STEFANOV, W.L. & C. REDMANN (2010): *Applied Remote Sensing for Urban Planning, Governance and Sustainability*. Springer Verlag, Berlin, 312 pp.

NETZBAND, M. & A. RAHMAN (2009): Physical Characterisation of Deprivation in Cities. How can remote Sensing help to profile poverty (slum dwellers) in the megacity of Delhi/India? In: *Proceedings of 2009 Urban Remote Sensing Joint Event*, 20-22 May 2009, Shanghai, China, 5 pp.

NEUBERT, M. & G. MEINEL (2003): Evaluation of Segmentation Programs for High Resolution Remote Sensing Applications. In: SCHROEDER, M., JACOBSEN, K. & C. HEIPKE (eds.): *Proceedings of the*

Joint ISPRS/EARSeL Workshop "High Resolution Mapping from Space 2003", 6-8 October, 2003, Hannover, Germany, 8 pp. (published on CD-ROM).

NEUBERT, M. (2005): Bewertung, Verarbeitung und segmentbasierte Auswertung sehr hoch auflösender Satellitenbilddaten vor dem Hintergrund landschaftsplanerischer und landschaftsökologischer Anwendungen. Doctoral Dissertation, Technical University (TU) Dresden, Germany, 152 pp.

NEUBERT, M., HEROLD, H. & G. MEINEL (2006): Evaluation of remote sensing image segmentation quality — further results and concepts. In: *Proceedings of the 1st International Conference on Object-based Image Analysis (OBIA 2006)*, 4-5 July 2006, Salzburg, Austria, 6 pp.

NEUBERT, M. & H. HEROLD (2008): Assessment of Remote Sensing Image Segmentation Quality. In: HAY, G.H., BLASCHKE, T. & D. MARCEAU (eds.): *Proceedings of the GEOBIA 2008 — Pixels, Objects, Intelligence. GEOgraphic Object Based Image Analysis for the 21st Century*, 5-8 August 2008, University of Calgary, Calgary, Alberta, Canada, ISPRS vol. no. XXXVIII, part 4/C1, archives ISSN no.1682-1777, 5 pp.

NICHOL, J.E. (1996): High-resolution surface temperature patterns related to urban morphology in a tropical city: A satellite-based study. In: *Journal of Applied Meteorology*, vol. 35, no. 1, pp. 135-146.

NICHOL, J.E. & C.M. LEE (2005): Urban vegetation monitoring in Hong Kong using high resolution Multispectral images. In: International Journal of Remote Sensing, vol. 23, pp. 1639-1649.

NICHOL, J. & M.S. WONG (2007): Remote sensing of urban vegetation life form by spectral mixture analysis of high-resolution IKONOS satellite images. In: International Journal of Remote Sensing, vol. 28, no. 5, pp. 985-1000.

NICHOL, J.E. & M.S. WONG (2007): ASSESSING URBAN ENVIRONMENTAL QUALITY WITH MULTIPLE PARAMETERS. IN: WENG, Q. & D.A. QUATTROCHI (eds.) (2007): *Urban Remote Sensing*. Taylor & Francis, New York, pp. 253-268.

NIEBERGALL, S., LOEW, A. & W. MAUSER (2007): Object-oriented analysis of very high-resolution QuickBird data for mega city research in Delhi/India. In*: Proc. of Urban Remote Sensing Joint Event (URS)*, 11-13 April 2007, Paris, France, 8 pp., IEEE 07EX1577, ISBN 1-4244-0712-5.

NIEBERGALL, S., LOEW, A. & W. MAUSER (2008): Mapping Different Settlement Types within Megacity Delhi Using VHR QuickBird Data: A Combination of Object-Oriented and Per Pixel Classification. In: *Proceedings of 28th EARSeL Symposium "Remote Sensing for a Changing Europe"*, Istanbul, Turkey, 2-7 June 2008.

NIEBERGALL, S., LOEW, A. & W. MAUSER (2009): Integrative Assessment of Informal Settlements Using VHR Remote Sensing Data — The Delhi Case Study. In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTARS)*, vol. 1, issue 3, pp. 193-205. ISSN 1939-1404, DOI: 10.1109/JSTARS.2008.2007513, URL: http://ieeexplore.ieee.org/xpl/articleDetails.jsp?arnumber=4703185 (access December 2014).

NOBREGA, R.A.A., O'HARA, C.G. & J.A. QUINTANILHA (2006): Detecting Roads in Informal Settlements Surrounding Sao Paolo City by Using Object-based Classification. In: *Proc. 1st Int. Conf. on Object-Based Image Analysis (OBIA)*, 4-5 July 2006, Salzburg, Austria, 6 pp.

NUSSBAUM, S., NIEMEYER, I. & M.J. CANTY (2005): Feature Recognition in the Context of Automated Object-Oriented Analysis of Remote Sensing Data Monitoring the Iranian Nuclear Sites. In: *Proc. of SPIE Europe Symposium Optics and Photonics for Defence and Security 2005*, 26-28 September 2005, Bruges, Belgium, vol. 5988, 598805, 9 pp.

NUSSBAUM, S., NIEMEYER, I. & M.J. CANTY (2006): SEaTH — A new tool for automated feature extraction in the context of object-based image analysis. In: *Proc. of 1st Int. Conf. on Object-Based Image Analysis (OBIA)*, 4-5 July 2006, Salzburg, Austria, 6 pp., ISPRS vol. no. XXXVI-4/C42; ISSN 1682-1777.

NUSSBAUM, S. & G. MENZ (2008): Object-Based Image Analysis and Treaty Verification. New Approaches in Remote Sensing — Applied to Nuclear Facilities in Iran. Springer Science+Business Media B.V., Berlin, 172 pp.

OGASHAWARA, I. & V. DA SILVA BRUM BASTOS (2012): A Quantitative Approach for Analyzing the Relationship between Urban Heat Islands and Land Cover. In: *Remote Sensing*, vol. 4, no. 11, pp. 3596-3618, DOI: 10.3390/rs4113596.

OZDARICI, A. & M. TURKER (2006): Filed-based Classification of Agricultural Crops Using Multi-Scale Images. In: *Proc. 1st Int. Conf. on Object-Based Image Analysis (OBIA)*, 4-5 July 2006, Salzburg, Austria, 7 pp.

PAL, N.R. & S.K. PAL (1993): A review on image segmentation techniques. In: *Pattern Recognition*, vol. 26, pp. 1277-1294.

PARAI, A., BENHART, J.E. & W.C. RENSE (1994): Water Supply in Selected Mega Cities of Asia. In: DUTT, A.K., COSTA, F.J., AGGARWAL, S. & A.G. NOBLE (eds.): *The Asian City: Processes of Development, Characteristics and Planning.* Kluwer Academic Publishers, Dordrecht, The Netherlands, pp. 205-212.

PECK, L. (2005): *Delhi. A thousand years of building*. Roli Books, Delhi, 328 pp.

PÉTERI, R. & T. RANCHIN (2008): Road networks Derived from High Spatial Resolution Satellite Remote Sensing Data. In: WENG, Q. (ed.): *Remote Sensing of Impervious Surfaces*. Taylor & Francis CRC Press, Boca Raton, pp. 215-236.

PHINN, S., STANFORD, M., SCARTH, P., MURRAY, A.T. & P.T. SHYY (2002): Monitoring the composition of urban environments based on the vegetation-impervious surface-soil (VIS) model by subpixel analysis techniques. In: *International Journal of Remote Sensing*, vol. 23, pp. 4131-4153.

PLANETEARTH (2005): Megacities – our global urban future. Earth Sciences for Society Foundation, Leiden, Netherlands, 16 pp. URL: www.yearofplanetearth.org (access August 2008).

POHL, C. & J.L. VAN GENDEREN (1998): Multisensor Image Fusion in Remote Sensing: Concepts, Methods and Applications. In: *International Journal of Remote Sensing*, vol. 5, pp. 823-854.

POURSANIDIS, D., CHRYSOULAKIS, N. & Z. MITRAKA (2015): Landsat 8 vs. Landsat 5: A comparison based on urban and peri-urban land cover mapping. In: *International Journal of Applied Earth Observation and Geoinformation*, vol. 2, no. 35, pp. 259-269.

POZZI, F. & C. SMALL (2002): Vegetation and Population Density in Urban and Suburban Areas in the U.S.A. In: *Proceedings of 3rd International Symposium of Remote Sensing of Urban Areas*, June 2002, Istanbul, Turkey, pp. 489-496.

QIU, F., WOLLER, K.L. & R. BRIGGS (2003): Modeling Urban Population Growth from Remotely Sensed Imagery and TIGER GIS Road Data. In: *Photogrammetric Engineering*, vol. 69, no. 9, pp. 1031-1042.

RADNAABAZAR, G., KUFFER, M. & P. HOFSTEE (2004): Monitoring the development of informal settlements in Ulaanbaatar, Mongolia. In: SCHRENK, M. (ed.): *CORP 2004 & Geomultimedia04*, February 2004, Vienna, Austria, pp. 333-339.

RAHMAN, A., AGGARWAL, S.P. NETZBAND, M. & S. FAZAL (2010): Monitoring Urban Sprawl Using Remote Sensing and GIS Techniques of a Fast Growing Urban Centre, India. In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 4, no. 1, pp. 1939-1404, DOI: 10.1109/JSTARS.2010.2084072.

RAMACHANDRAIAH, C. (2001): Drinking Water as a Fundamental Right. In: *Economic and Political Weekly*, Feb. 24, pp. 619-621.

RAO, P. K. (1972): Remote sensing of urban "heat islands" from an environmental satellite. In: *Bull. Amer. Meteor. Soc.*, vol. 53, pp. 647-648.

RASHED, T. & J. WEEKS (2003): Exploring the spatial association between measures from satellite imagery and patterns of urban vulnerability to earthquake hazards. In: *Proceedings of 4th International Symposium Remote Sensing of Urban Areas (URS)*, 27-29 June 2003, Regensburg, Germany, pp.144-152.

RASHED, T. & C. JUERGENS (eds.) (2010): *Remote Sensing of Urban and Suburban* Areas. Springer, Dordrecht, Heidelberg, London, New York, 352 pp.

REES, W.G. (2001): *Physical Principles of Remote Sensing*. Cambridge University Press, 2nd ed., Cambridge, 372 pp.

REGO, L.F.G. & B. KOCH (2003): Automatic Classification of Land Cover with High Resolution Data of the Rio de Janeiro City Brazil. In: *Proceedings of 2nd GRSS/ISPRS Joint Workshop on "Data Fusion and Remote Sensing over Urban Areas"*, 22-23 May 2003, Berlin, Germany, pp. 172-176.

RICHARDS, J.A. & X. JIA (2006): *Remote Sensing Digital Image Analysis. An Introduction.* Springer, 5th ed., Berlin, Heidelberg, and New York, 439 pp.

RINDFUSS, R.R. & P.C. STERN (1998): Linking Remote Sensing and Social Science: The Need and the Challenges. In: LIVERMAN, D., MORAN, E.F., RINDFUSS, R.R. & P.C. STERN (eds.): *People and Pixels. Linking Remote Sensing and Social Science*. National Academy Press, Washington, D.C., pp. 1-27.

ROESSNER, S., SEGL, K., HEIDEN, U. & H. KAUFMANN (2001): Automated differentiation of urban surfaces based on airborne hyperspectral imagery. In: *IEEE Transactions on Geoscience and Remote Sensing,* vol. 39, no. 7. pp. 1525-1532.

ROGERS, D., EMWANU, T. & T. ROBINSON (2006): Poverty Mapping in Uganda Using Socio-economic, Environmental and Satellite Data. In: *Pro-Poor Livestock Policy Initiative (PPLPI) Features — A Living from Livestock*, 5 pp. URL: http://www.fao.org/ag/againfo/programmes/en/pplpi/docarc/feature03_povertyuganda.pdf (access December 2014).

ROSENFIELD, G.H. & K. FITZPATRICK-LINS (1986): A coefficient of agreement as a measure of thematic classification accuracy. In: *Photogrammetric Engineering and Remote Sensing*, vol. 52, pp. 223-227.

ROSSI, L. (2003): Satellite High Resolution New Applications: QuickBird. In: *Proc. of the EFITA 2003 Conference*, 5-9 July 2003, Debrecen, Hungary, pp. 388-392.

ROTH, M., OKE, T.R. & W.J. EMERY (1989): Satellite derived urban heat islands from three coastal cities and the utilisation of such data in urban climatology. In: *International Journal of Remote Sensing*, vol. 10, pp. 1699-1720.

ROTH, A., HOFFMANN, J. & T. ESCH (2005): TerraSAR-X: How can high resolution SAR data support the observation of urban areas? In: *Proceedings of the ISPRS WG VII/1 "Human Settlements and Impact Ananlysis" 3rd International Symposium Remote Sensing and Data Fusion over Urban Areas (URBAN 2005) & 5th International Symposium Remote Sensing of Urban Areas (URS 2005)*, 14-16 March 2005, Tempe, AZ, USA, CD-ROM.

SABINS, F.F. (1996): Remote sensing: Principles and Interpretation. Freeman & Co., New York, 549 pp.

SARMA, B., REDDY, D., RAO, V. & M. GOHAIN (2003): Development of an Integrated Remote Sensing and GIS-based Decision Suport System for Planning and management of the Growth of Guwahati City, India. In: JÜRGENS, C. (eds.): *Proc. of the 4th International Symposium "Remote Sensing of Urban Areas"*, 27-29 June 2003, Regensburg, Germany, The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences Vol. XXXIV-7/W9 (CD-ROM), pp. 158-163.

SCHIEWE, J. (2002): Segmentation of high-resolution remotely sensed data — Concepts, applications and problems. In: *Proceedings of Symp. Geospatial Theory, Processing and Applications*, 9-12 July 2002, Ottawa, ON, Canada, 6 pp.

SCHNEIDER, A., FRIEDL, M.A., MCIVER, D.K. & C.E. WOODCOCK (2003): Mapping urban areas by fusing multiple sources of coarse resolution remotely sensed data. In: *Photogrammetric Engineering and Remote Sensing*, vol. 69, no. 12, pp. 1377-1386.

SCHUELER, T.R. (1994): The importance of imperviousness. In: *Watershed Protection Techniques*, vol. 1, no. 3, pp. 100-110.

SCHOLZ, F. (2002): Die Theorie der "fragmentierenden Entwicklung". *Geographische Rundschau*, vol. 54, no. 10, pp. 6-11.

SCHOWENGERDT, R.A. (1997): *Remote Sensing — Models and Methods for Image Processing*. Academic Press, 2nd edition, San Diego, 522 pp.

SECORD, J. & A. ZAKHOR (2007): Tree Detection in Urban Regions Using Aerial LiDAR and Image Data. In: *IEEE Geoscience and Remote Sensing Letters*, vol. 4, no. 2, pp. 196-200.

SELBACH, V. (2009): Wasserversorgung und Verwundbarkeit in der Megastadt Delhi/Indien. Doctoral Dissertation, University of Cologne, Germany, 262 pp., URL: http://kups.ub.uni-koeln.de/2860/ (access November 2014).

SHABAN, A. (2008): *Water Poverty in Urban India: A Study of Major Cities*. Tata Institute of Social Science, Mumbai, 21 pp., URL: http://jmi.ac.in/upload/publication/Water_Poverty_in_urban_India.pdf (access December 2009).

SHACKELFORD, A.K. & C.H. DAVIS (2003): Urban Road network Extraction from High-Resolution Multispectral Data. In: *Proc. 2nd GRSS/ISPRS Joint Workshop "Data Fusion and Remote Sensing over Urban Areas"*, 22-23 May 2003, Berlin, Germany, pp. 142-146.

SHAN, J. & A. SAMPATH (2007): Urban Terrain and Building Extraction from Airborne LIDAR Data. In: WENG, Q. & D.A. QUATTROCHI (eds.) (2007): *Urban Remote Sensing*. Taylor & Francis, New York, pp. 21-46.

SILVA, E.A. & K.C. CLARKE (2002): Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. In: *Computers, Environment and Urban Systems*, vol. 26, pp. 525-552.

SINGH, R. & T. KRAFFT (2007): Vulnerability With Respect to Water and Wastewater Sytem in Megacity Delhi. In: *Proc. of the 2nd International Congress on Environmental Planning and Management*, 5-7 August 2007, Technical University of Berlin, Germany, 4 pp.

SINGH, R., KRAAS, F., KRAFFT, T., LOEW, A., MAUSER, W., NIEBERGALL, S. & V. SELBACH (2007): A new approach to analyse water related vulnerability in Megacities: Case study of Delhi. In: *WHOCC Newsletter*, no. 10, Bonn, Germany, pp. 4-7.

SINGH, R. (2008): Wastewater Problems and Social Vulnerability in Megacity Delhi/India. Inaugural Dissertation, University of Cologne, Germany, 404 pp., URL: kups.ub.uni-koeln.de/2819/1/Thesis_reena_singh.pdf (access December 2014).

SLIUZAS, R. (2008): Improving the Performance of Urban Planning and Management with Remote sensing systems. In: *Proc. of EARSeL Joint Workshop "Remote Sensing - New Challenges of High Resolution*", 5-7 March 2008, Bochum, Germany, 13 pp.

SLIUZAS, R., KERLE, N. & M. KUFFER (2008a): Object-oriented mapping of urban poverty and deprivation. In: *Proc. of the 4th Workshop of the EARSeL SIG on Developing Countries in Conjunction with 8th Workshop of the GISDECO*, 4-7 June 2008, Istanbul, Turkey, 13 pp.

SLIUZAS, R. & M. KUFFER (2008b): Analysing the spatial heterogeneity of poverty using remote sensing: typology of poverty areas using selected RS based indicators. In: *Proc. of EARSeL Joint Workshop "Remote Sensing - New Challenges of High Resolution*", 5-7 March 2008, Bochum, Germany, pp. 158-167.

SMALL, C. (1999): Estimation of Urban Vegetation Abundance by Linear Spectral Unmixing. In: *International Journal of Remote Sensing*, vol. 22, no. 7, pp. 1305-1334.

SMALL, C. & R.B. MILLER (2000): Spatiotemporal Monitoring of Urban Vegetation. In: *Proceedings of International Symposium on Remote Sensing of Environment*, 27-31 March 2000, Cape Town, South Africa, 5 pp.

SMALL, C. (2001): Estimation of urban vegetation abundance. In: *International Journal of Remote Sensing*, vol. 22, pp. 1305-1334.

SMALL, C. (2003): High spatial resolution spectral mixture analysis of urban reflectance. In: *Remote Sensing of Environment*, vol. 88, pp. 170-186.

SMALL, C. (2006): Comparative analysis of urban reflectance and surface temperature. In: WENG, Q. & D.A. QUATTROCHI (eds.): *Remote Sensing of Environment, vol. 104, Special Issue on Thermal Remote Sensing of Urban Areas*, pp. 168-189.

SMALL, C. (2007): Comparative Analysis of Urban Vegetation Scale and Abundance. In*: Proc. of Urban Remote Sensing Joint Event (URS)*, 11-13 April 2007, Paris, France, 10 pp., IEEE 07EX1577, ISBN 1-4244-0712-5.

SMITH, G.M. & A. HOFFMANN (2001): An Object Based Approach to Urban feature Mapping. In: JUERGENS, C. (ed.): *Proceedings of t*he *2nd International Symposium Remote Sensing of Urban Areas*, 22-23 June 2001, Regensburg, Germany, Regensburger Geographische Schriften, no. 35, pp. 100-106 (supplemented on CD ROM).

SMITS, P.C., DELLEPIANE, S.G. & R.A. SCHOWENGERDT (1999): Quality assessment of image classification algorithms for land-cover mapping: a review and proposal for a cost-based approach. In: *International Journal of Remote Sensing*, vol. 20, pp. 1461-1486.

SOERGEL, U. (ed.) (2010): Radar Remote Sensing of Urban Areas- Springer, Dordrecht, Heidelberg, London, New York, 278 pp.

SONG, C. (2008): Bayesian Spectral Mixture Analysis for Urban Vegetation. In: WENG, Q. & D.A. QUATTROCHI (eds.) (2007): *Urban Remote Sensing*. Taylor & Francis, New York, pp. 91-108.

SONI, A. (2000): Urban Conquest of Outer Delhi: Beneficiaries, Intermediaries and Victims – The Case of the Mehrauli Countryside. In: DUPONT, V., TARLO, E. & D. VIDAL (eds.): *Delhi. Urban Space and Human Destinies*, Manohar, Delhi, pp. 75-96.

SOUZA, I. DE MARCELHAS E, PEREIRA, M.N. & M. DE L.N.O. KURKDJIAN (2002): Evaluation of High Resolution Satellite Image for Urban Population Estimation. In: *Proc. 3rd International Symposium on Remote Sensing of Urban Areas*, 11-13 June 2002, Istanbul, Turkey, pp. 147-152.

STAHEL, W.A. (2002): Statistische Datenanalyse*. Eine Einführung für Naturwissenschaftler*, 4. Auflage, Vieweg Verlag, Braunschweig/Wiesbaden, 389 pp.

STEEL, A.M., BARNSLEY, M.J. & S.L. BARR (2001): Inferring urban land cover and land use through analysis of airborne LIDAR data. In: JUERGENS, C. (ed): *Proceedings of t*he *2nd International Symposium Remote Sensing of Urban Areas*, 22-23 June 2001, Regensburg, Germany, Regensburger Geographische Schriften, no. 35, pp. (supplemented on CD ROM).

STEFANOV, W.L., RAMSEY, M.S. P.R. CHRISTENSEN (2001): Monitoring urban land cover change: An expert system approach to land cover classification of semiarid to arid urban centers. In: *Remote Sensing of Environment*, vol. 77, pp. 173-185.

STEHMAN, S.V. (1997): Selecting and interpreting measures of thematic classification accuracy. In: *Remote Sensing of Environment*, vol. 62, pp. 77-89.

STEINNOCHER, K. (1997): Texturanalyse zur Detektion von Siedlungsgebieten in hochauflösenden panchromatischen Satellitendaten. In: *Proceedings AGIT IX Salzburg*, 02-04 July 1997, Salzburg, Austria, Salzburger Geographische Materialien, no. 24, pp. 143-152.

STEWART, G. & M. KUFFER (2007): Where are the poor? A disaggregation approach of mapping urban poverty. In: SCHRENK, M., POPOVICH, V.V. & J. BENEDIKT (Eds.): *Proceedings of REAL CORP 007*, 20-23 May 2007, Vienna, Austria, pp. 847-858.

STILLA, U. & U. SOERGEL (2007): Reconstruction of Building Extraction in SAR Imagery of Urban Areas. In: WENG, Q. & D.A. QUATTROCHI (eds.) (2007): *Urban Remote Sensing*. Taylor & Francis, New York, pp. 47-68.

STILLA, U., HINZ, S., HEDMAN, K. & B. WESSEL (2008): Road Extraction from SAR Imagery. In: WENG, Q. (ed.): *Remote Sensing of Impervious Surfaces*. Taylor & Francis CRC Press, Boca Raton, pp. 179-214.

STORY, M. & R.G. CONGALTON (1986): Accuracy Assessment: A User´s Perspective. In: *Photogrammetric Engineering & Remote Sensing*, vol. 52, no. 3, pp. 397-399.

STREUTKER, D.R. (2002): A remote sensing study of urban heat island of Houston, Texas. In: *International Journal of Remote Sensing*, vol. 23, no. 13, pp. 2595-2608.

STROBEL, R. (1997): Bombay, Delhi, Bangalore — drei indische Metropolen im Zeichen wirtschaftlicher Liberalisierung. In: FELDBAUER, P., HUSA, K., PILZ, E. & I. STACHER (eds.): *Mega-Cities. Die Metropolen des Südens zwischen Globalisierung und Fragmentierung*. Historische Sozialkunde, vol. 12, pp. 67-89.

SUGUMARAN, R., GERJEVIC, J. & M. VOSS (2008): Transportation Infrastructure Extraction Using Hyperspectral Remote Sensing. In: WENG, Q. (ed.): *Remote Sensing of Impervious Surfaces*. Taylor & Francis CRC Press, Boca Raton, pp. 163-178.

SUMER, E. & M. TURKER (2006): An Integrated Earthquake Damage Detection System. In: *Proc. 1st Int. Conf. on Object-Based Image Analysis (OBIA)*, 4-5 July 2006, Salzburg, Austria, 6 pp.

SUTTON, P. (1997): Modeling population density with night-time satellite imagery and GIS. In: *Computers, Environment and Urban Systems*, vol. 21, no. 3-4, pp. 227-244.

SUTTON, P., ROBERTS, D., ELVIDGE, C. & H. MEIJ (1997): A comparison of nighttime acquired satellite imagery and population density for the continental United States. In: *Photogrammetric Engineering and Remote Sensing*, vol. 63, no. 11, pp. 1303-1313.

SUTTON, P.C., TAYLOR, M.J., ANDERSON, S. & C.D. ELVIDGE (2007): Sociodemographic Characterization of Urban Areas Using Nighttime Imagery, Google Earth, Landsat, and "Social" Ground Truthing. In: WENG, Q. & D.A. QUATTROCHI (eds.) (2007): *Urban Remote Sensing*. Taylor & Francis, New York, pp. 291-310.

TAPAS, R.M., KERLE, N., VAN WESTEN, C.J., JETTEN, V. & K.V. KUMAR (2012): Object-oriented analysis of multi-temporal panchromatic images for creation of historical landslide inventories. In: *ISPRS Jorurnal Of Photogrammetry and Remote Sensing*, vol 67, no. 67, pp. 105-119.

TARLO, E. (2000): Welcome to History: A Resettlement Colony in the Making. In: DUPONT, V., TARLO, E. & D. VIDAL (eds.): *Delhi. Urban Space and Human Destinies*, Manohar, Delhi, pp. 51-74.

TATEM, A.J., NOOR, A.M. & S.I. HAY (2005): Assessing the Accuracy of Satellite Derived Global and National Urban Maps in Kenya. In: *Remote Sensing of Environment*, vol. 13, no. 7, 11 pp.

TAUBENBÖCK, H., KEMPER, T., ROTH, A. & S. VOIGT (2006): Assessing Vulnerability in Istanbul: An Example to Support Disaster Management with Remote Sensing at DLR-ZKI. In: *Proceedings of German Turkish Joint Geodetic Days*, Fith International Symposium, ISBN 3-9809030-4-4, Technical University Berlin, Germany, 9 pp.

TAUBENBÖCK, H. & A. ROTH (2007): A Transferable and Stable Object Oriented Classification Approach in Various Urban Areas and Various High Resolution Sensors. In: *Proc. of Urban Remote Sensing Joint Event (URS)*, 11-13 April 2007, Paris, France, 7 pp., IEEE 07EX1577, ISBN 1-4244-0712-5.

TAUBENBÖCK, H., ROTH, A. & S. DECH (2007): Vulnerability assessment using remote sensing: The earthquake prone megacity Istanbul, Turkey. In: *Proceedings of International Symposium on Remote Sensing and Environment*, San Jose, Costa Rica, 5 pp.

TAUBENBÖCK, H. (2008): Vulnerabilitätsabschätzung der erdbebengefährdeten Megacity Istanbul mit Methoden der Fernerkundung. Doctoral Dissertation, University of Würzburg, Germany, 178 pp.

TAUBENBÖCK, H., POST, J., ROTH, A., ZOSSEDER, K., STRUNZ, G. & S. DECH (2008): A conceptual vulnerability and risk framework as outline to identify capabilities of remote sensing. In: *Natural Hazards and Earth System Sciences*, vol. 8, no. 3, pp. 409-420, URL: http://www.nat-hazards-earth-syst-sci.net/8/409/2008/ nhess-8-409-2008.html (access July 2009).

TAUBENBÖCK, H., WURM, M., SETIADI, N., GEBERT, N., ROTH, A., STRUNZ, G., BIRKMANN, J. & S. DECH (2009): Integrating Remote Sensing and Social Science — The correlation of urban morphology with socioeconomic parameters. In: *Proceedings of 2009 Urban Remote Sensing Joint Event*, 20-22 May 2009, Shanghai, China, 7 pp.

TAUBENBÖCK, H., WEGMANN, M., ROTH, A., MEHL, H. & S. DECH (2009a): Urbanization in India — Spatiotemporal analysis using remote sensing data. In: *Computers, Environment and Urban Systems,* vol. 33, pp. 179-188.

TAUBENBÖCK, H., FELBIER, A., ESCH, T., ROTH, A. & S. DECH (2012): Pixel-based classification algorithm for mapping urban footprints from radar data — a case study for RADARSAT-2. In: CAN., J. (ed.): *Remote Sensing*, vol. 38, no.3, pp.211-222.

TILTON, J.C. (1998): Image segmentation by region growing and spectral clustering with a natural convergence criterion. In: *Proceedings IGARSS*, 6-10 July 1998, Seattle, WA, vol. 4, pp. 1766-1768.

TIWARI, P.S. & H. PANDE (2011): LIDAR Remote Sensing Applications in Automated Urban Feature Extraction. In: WANG, C.-C. (ed.) (Laser Scanning, Theory and Applications. InTech, DOI: 10.5772/14983, 576 pp. URL: http://www.intechopen.com/books/laser-scanning-theory-and-applications/lidar-remote-sensing-applications-in-automated-urban-feature-extraction (access January 2015).

TOBLER, W.R. (1970): A computer Model Simulating Urban Growth in the Detroit Region. In: *Economic Geography*, vol. 46, pp. 234-240.

THOMLINSON, J.R., BOLSTAD, P.V. & W.B. COHEN (1999): Coordinating methodologies for scaling landcover classifications from site-specific to global: steps toward validating global map products. In: *Remote Sensing of Environment*, vol. 70, pp. 16-28.

TOUTIN, T. & P. CHENG (2002): QuickBird – A Milestone for High-Resolution Mapping. In: *Earth Observation Magazine* – The Magazine for Geographic, Earth, Mapping Information, vol. 11, no. 4, pp. 14-18.

TRICE, B. (2006): Urban Management Challenges in Mega-Cities: A Survey of Catastrophic Events in the Developing and Developed World. In: *urban action*: A Journal of Urban Affairs, pp. 69-79.

TRIVEDI, S.M., YADAV, B.R., GUPTA, N., CHANDRASEKHARAN, H. & K. RAMACHANDRAN (2001): Effects of urbanization on changes in groundwater quantity and quality in Delhi State, India. In: *Impact of*

Human Activity on Groundwater Dynamics (Proceedings of a Symposium held during 6th IAHS Scientific Assembly at Maastricht, The Netherlands, July, 2001), IAHS publish. no. 269.

TUPIN, F. (2003): Extraction of §D information using overlay detection on SAR images. In: In: *Proc. 2nd GRSS/ISPRS Joint Workshop "Data Fusion and Remote Sensing over Urban Areas"*, 22-23 May 2003, Berlin, Germany, pp. 72-75.

TURKSTRA, J. & M. RAITHELHUBER (2004): Urban Slum Monitoring. 13 pp. URL: http://gis.esri.com/library/userconf/proc04/docs/pap1667.pdf (access December 2014).

TURNER, B.L. (1991): Thoughts on linking the physical and human sciences in the study of global environmental change. In: *Research and Exploration*, vol. 7, pp. 133-135.

TURNER II, B.L. (1997): Socializing the pixel in LUCC. In: *LUCC Newsletter*, no. 1, pp. 10.11.

TURNER II, B.L. (1998): Frontiers of Exploration: Remote Sensing and Social Science Research. In: *Proceedings of Pecora 13 Symposium, Human Interaction with the Environment: Perspectives from Space*, 20-22 August 1996, Sioux Falls, SD, pp. 15-19.

TUYAHOV, A.J., DAVIES, C.S. & R.K. HOLZ (1973): Detection of urban blight using remote sensing techniques. In: *Remote Sensing of Earth Resources*, vol. 2, pp. 213-226.

UNITED NATIONS ENVIRONMENT PROGRAM (2002): GEO: Global Environment Outlook-3: Past, present and future perspectives. Earthscan, London, 480 pp.

UNFPA (1996): The State of the World Population 1996: Changing Places: Population, Development and the Urban Future. New York, 100 pp.

UNFPA (United Nations Population Fund) (2007): State of the World Population 2007. New York, 99 pp. URL: http://www.unfpa.org/publications/state-world-population-2007 (access November 2014).

UNITED NATIONS (1997): Population Growth and Policies in Mega-Cities: Bangkok. Population Policy Paper, no. 10, New York, 47 pp.

UNITED NATIONS (2002): World Urbanization Prospects: The 2001 Revision. Data Tables and Highlights. New York, 190 pp. URL: http://www.un.org/esa/population/publications/wup2001/wup2001dh.pdf (access November 2014).

UNITED NATIONS (2004): World Urbanization Prospects: The 2003 Revision. New York, 323 pp.

UNITED NATIONS (2005): A Home in the City. Task Force on Improving the Lives of Slum Dwellers. Millennium Project 2005. Earthscan, London and Sterling, Virginia, 184 pp. URL: http://www.unmillenniumproject.org/documents/Slumdwellers-complete.pdf (access November 2014)

UNITED NATIONS (2007): World Population Prospects: The 2006 Revision. New York, 21 pp. URL: http://www.un.org/esa/population/publications/wpp2006/English.pdf (access November 2014).

UNITED NATIONS (2008a): Urban Population, Development and the Environment 2007. New York, 2 pp. URL: http://unpopulation.org (access November 2014).

UNITED NATIONS (2008b): World Urbanization Prospects: The 2007 Revision. New York, 244 pp. URL: http://www.un.org/esa/population/publications/wup2007/2007WUP_Highlights_web.pdf (access November 2014).

UNITED NATIONS (2014): World Urbanization Prospects: The 2014 Revision. Highlights. New York, 32 pp. URL: http://esa.un.org/unpd/wup/Highlights/WUP2014-Highlights.pdf (access December 2014) and http://esa.un.org/unpd/wup/CD-ROM/ (access January 2015).

UN-HABITAT (2003a): Challenge of Slums — Global Report on Human Settlements 2003. Nairobi, New York, 310 pp.

UN-HABITAT (2003b): Slums of the World: The Face of Urban Poverty in the New Millennium? Nairobi, 90 pp.

UN-HABITAT (2004): Sustainable Urbanisation. Achieving Agenda 21, vol. 20, Nairobi, 31 pp.

UN-HABITAT (2006): State of the World's Cities Report 2006/2007. Nairobi, 204 pp.

UN-HABITAT (2012): State of the World´s Cities 2010/2011 – Bridging the Urban Divide. Earthscan, London and Sterling, Virginia, 244 pp. URL: http://mirror.unhabitat.org/pmss/listItemDetails.aspx?publicationID=2917 (access January 2015).

UN-HABITAT (2012a): State of the World´s Cities 2012/2013 – Prosperity of Cities. Nairobi, Kenya, 152 pp. URL: http://mirror.unhabitat.org/pmss/listItemDetails.aspx?publicationID=3387 (access January 2015).

UN- HABITAT (2013): Global Report on Human Settlements 2013 – Planning and Design for Sustainable Urban Mobility. Earthscan, Abingdon and New York, 348 pp. URL: http://mirror.unhabitat.org/pmss/listItemDetails.aspx?publicationID=3503 (access January 2015).

UN POPULATION DIVISION (2001): *World Urbanization Prospects: The 2001 Revision*. URL: http://www.un.org/esa/population/publications/wup2001/WUP2001report.htm (access November 2014)

URL 1: http://www.yearofplanetearth.org (access November 2014)

URL 2: https://www.ugec.org (access November 2014)

URL 3: http://www.megacities.uni-koeln.de (access November 2014)

URL 4: http://www.geographie.uni-koeln.de/megacities-spp (access October 2014)

URL 5: http://www.emerging-megacities.org (access November 2014)

URL 6: http://www.risk-habitat-megacity.ufz.de/index.php?en=15003 (access November 2014)

URL 7: http://www.satimagingcorp.com/satellite-sensors/quickbird/ (access November 2014)

URL 8: http://www.destatis.de (access November 2014)

URL 9: http://www.censusindia.net/ (access November 2014)

URL 10: http://tardis.ed.ac.uk/~kate/qmcweb/qcont.htm (access October 2014)

URL 11: http://www.analytictech.com/mb313/principl.htm (access November 2014)

URL 12: http://www.britannica.com/EBchecked/topic/564172/statistics (access December 2014)

URL 13: http://eo1.usgs.gov/sensors/hyperion (access November 2014)

URL 14: http://www.esa.int/Our_Activities/Observing_the_Earth/Proba-1 (access November 2014)

URL 15: http://aviris.jpl.nasa.gov (access November 2014)

URL 16: http://www.eumetsat.int/Home/index.htm (access September 2009)

URL 17: http://kingfish.coastal.edu/marine/Animations/Images/Electromagnetic-Spectrum-3.png (access October 2014)

URL 18: http://www.definiens.com/ (access November 2014)

URL 19: https://www.digitalglobe.com/sites/default/files/DG_GeoEye1.pdf (access January 2015)

URL 20: https://www.digitalglobe.com/about-us/content-collection (access January 2015)

URL 21: http://www.copernicus.eu/ (access January 2015)

URL 22: http://esa.un.org/unpd/wup/Maps/CityDistribution/CityPopulation/CityPop.aspx (access December 2014)

URL 23: http://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS (access January 2015)

VAN DE VOORDE, T., DE GENST, W., CANTERS, F., STEPHENNE, N., WOLFF, E. & M. BINARD (2004): Extraction of land use / land cover – related information from very high resolution data in urban and suburban areas. In: *Remote Sensing in Transaction*, pp. 237-244, ISBN 90 5966 007 2.

VOLPE, F. & L. ROSSI (2003): QuickBird high resolution satellite data for urban applications. In: *Proc. of 2nd GRSS/ISPRS Joint Workshop on Data Fusion and Remote Sensing Over Urban Areas*, Berlin, Germany, pp. 1-3.

VRABEL, J. (1996): Multispectral Imagery Band Sharpening Study. In: *Photogrammetric Engineering & Remote Sensing*, vol. 62, no. 9, pp. 1075-1083.

WAGROWSKI, D.M. & R.A. HITES (1997): Polycyclic aromatic hydrocarbon accumulation in urban, suburban and rural vegetation. In*: Environmental Science & Technology*, vol. 31, no. 1, pp. 279-282.

WANG, L. & C. WU (2010): Population estimation using remote sensing and GIS technologies. In: *International Journal of Remote Sensing*, vol.31, no. 21, pp. 5569-5570.

WEBSTER, C.J. (1995): Urban morphological fingerprints. In: *Environment and Planning B*, vol. 22, pp. 279-297.

WEEKS, J. R. (2001): The Role of Spatial Analysis in Demographic Research. In: GOODCHILD, M.F. & D.G. JANELLE (eds.): *Spatially Integrated Social Science: Examples in Best Practice*. Oxford University Press, New York, 31 pp.

WELCH, R. (1982): Spatial Resolution Requirements for Urban Studies. In: *International Journal of Remote Sensing*, vol. 3, no. 2, pp. 139-146.

WENG, Q., LU, D. & J. SCHUBRING (2004): Estimation of land surface temperature-vegetation abundance relationship for urban heat island studies. In: *Remote Sensing for Environment*, vol. 89, no. 4, pp. 467-483.

WENG, Q. & D.A. QUATTROCHI (eds.) (2006): Special Issue on Thermal Remote Sensing of Urban Areas. In: *Remote Sensing of Environment,* vol. 104, pp. 119-122.

WENG, Q. & D.A. QUATTROCHI (eds.) (2007): *Urban Remote Sensing*. Taylor & Francis, New York, 432 pp.

WENG, Q. (2008): Remote Sensing of Impervious Surfaces: An Overview. In: WENG, Q. (ed.): *Remote Sensing of Impervious Surfaces*. Taylor & Francis CRC Press, Boca Raton, pp. xv-xxv.

WENG, Q. (2009): Thermal infrared remote sensing for urban climate and environmental studies: Methods, applications, and trends. In: *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 64, no. 4, pp. 335-344, DOI: 10.1016/j.isprsjprs.2009.03.007.

WENG, Q. (2012): Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. In: *Remote Sensing of Environment*, vol. 117, no. 2, pp. 34-49, DOI:10.1016/j.rse.2011.02.030.

WENG, Q. (ed.) (2014): Global Urban Monitoring and Assessment Through Earth Observation. Taylor & Francis/CRC Press, Boca Raton, FL, USA, 440 pp.

WORLD HEALTH ORGANIZATION (WHO) (2003): *The Right to Water*. Geneva, 43 pp. URL: http://www.who.int/water_sanitation_health/en/righttowater.pdf (access December 2014).

WU, C. & A.T. MURRAY (2007): Population Estimation Using Landsat Enhanced Thematic Mapper Imagery. In: *Geographical Analysis*, vol. 39, pp. 26-43.

WU, J.G., JELINSKI, D.E., LUCK, M. & P.T. TUELLER (2000): Multiscale analysis of landscape heterogeneity: Scale variance and pattern metrics. In: *Geographic Information Sciences*, vol. 6, no.1, pp. 6-19.

WYATT, B.K., GREATOREX-DAVIES, J.N., HILL, M.O., PARR, T.W., BUNCE, R.G.H. & R.M. FULLER (1993): *Comparison of land cover definitions*. Countryside 1990 series, vol. 3, Report to the Dept. of the Environment, Institute of Terrestrial Ecology (ITE), Natural Environment Research Council, Cambridge, 131 pp.

XIAN, G. (2007): Assessing Urban Growth with Subpixel Impervious Surface Coverage. In: WENG, Q. & D.A. QUATTROCHI (eds.): *Urban Remote Sensing*. Taylor & Francis, New York, pp. 179-199.

XIAN, G. & M. CRANE (2006): An analysis of urban thermal characteristics and associated land cover in Tampa Bay and Las Vegas using Landsat satellite data. In: *Remote Sensing of Environment*, vol. 104, no. 2, pp. 147-156.

XIAOXIA, S., JIXIAN, Z. & L. ZHENGJUN (2005): A Comparison of Object-Oriented and Pixel-Based Classification Approaches Using QuickBird Imagery. In: *Proceedings of International Symposium on Spatio-temporal Modeling, Spatial Reasoning, Analysis, Data Mining and Data Fusion*, 27-29 August 2005, Beijing, China, 5 pp.

XIE, Y., SHA, Z. & M. YU (2008): Remote sensing imagery in vegetation mapping: a review. In: *Journal of Plant Ecology*, vol. 1, no. 1, pp. 9-23.

YAGER, R.R., NGUYEN, H.T., TONG, R.M. & S. OVCHINNIKOV (eds.) (1987): *Fuzzy sets and applications: Selected papers by L.A. Zadeh.* John Wiley & Sons, 684 pp.

YANG, L., HUANG, C., HOMER, C.G., WYLIE, B.K. & M.J. COAN (2003): An approach for mapping large-scale impervious surfaces: synergistic use of Landsat-7 ETM+ and high spatial resolution imagery. In: *Canadian Journal of Remote Sensing*, vol. 29, pp. 230-240.

YANG, X. (ed.) (2011): Urban Remote Sensing: Monitoring, Synthesis and Modeling in the Urban Environment. John Wiley & Sons, Chichester, UK, 408 pp.

YIN, Z.-Y., WALCOTT, S., KAPLAN, B., CAO, J., LIN, W., CHEN, M., LIU, D. & Y. NING (2005): An analysis of the relationship between spatial patterns of water quality and urban development in Shanghai, China. In: *Computers, Environment and Urban Systems*, vol. 29, pp. 197-221.

YUAN, F. & M.E. BAUER (2006): Mapping Impervious Surface Area Using High Resolution Imagery: A Comparison of Object-Based and Per Pixel Classification. In: *Proceedings of ASPRS 2006 Annual Conference*, 01-05 May 2006, Reno, Nevada, 8 pp.

YUSOF, J., STUART, N., REYES-FIRPO, P. & J. BRENNAN (2008): A Combined Analysis of Digital Map and Remote Sensing Data to Create a More Complete Inventory of Green and Open Spaces in Kuala Lumpur. In: *Proc. of the 4th Workshop of the EARSeL SIG on Developing Countries in Conjunction with 8th Workshop of the GISDECO*, 4-7 June 2008, Istanbul, Turkey, 10 pp.

ZADEH, L.A. (1965): Fuzzy sets. In: *Information and Control*, vol. 8, pp. 338-353.

ZADEH, L.A. (1973): Outline of a new approach to the analysis of complex systems and decision processes. In: *IEEE Transactions on Systems, Man, and Cybernetic*, SMC-3, no. 1, pp. 28-44.

ZERAH, M.H. (2000): Water — Unreliable supply in Delhi. Manohar Publishers, New Delhi, 196 pp.

ZHANG, H., FRITTS, J.A. & S.A. GOLDMAN (2005): A Co-Evaluation Framework for Improving Segmentation Evaluation. In: *SPIE Signal Processing and Target Recognition XIV*, pp.420-430.

ZHANG, Q. & I. COULOIGNER (2006): Automated Road Network Extraction from High resolution Multi-spectral Imagery. In: *Proc. ASPRS 2006 Annual Conference*, 1-5 may 2006, reno, Nevada, 10 pp.

ZHANG, L., HUANG, X., HUANG, B. & P. LI (2006): A Pixel Shape Index Coupled With Spectral Information for Classification of High Spatial Resolution Remotely Sensed Imagery. In: *IEEE Transactions on Geoscience and Remote Sensing*, vol. 44, no. 10, pp. 2950-2961.

ZHANG, Y. & T. MAXWELL (2008): Roof Mapping Using Fused Multiresolution Optical Satellite Images. In: WENG, Q. (eds.): *Remote Sensing of Impervious Surfaces*. Taylor & Francis CRC Press, Boca Raton, pp. 331-349.

ZHANG, Q., WANG, J., GONG, P. & P. SHI (2003): Study of urban spatial patterns from SPOT panchromatic imagery using textural analysis. In: *International Journal of Remote Sensing*, vol. 24, no. 21, pp. 4137-4160.

ZHOU, G. & J.A. KELMELIS (2007): True Orthoimage generation for Urban Areas with very High Buildings. In: WENG, Q. & D.A. QUATTROCHI (eds.) (2007): *Urban Remote Sensing*. Taylor & Francis, New York, pp. 3-20.

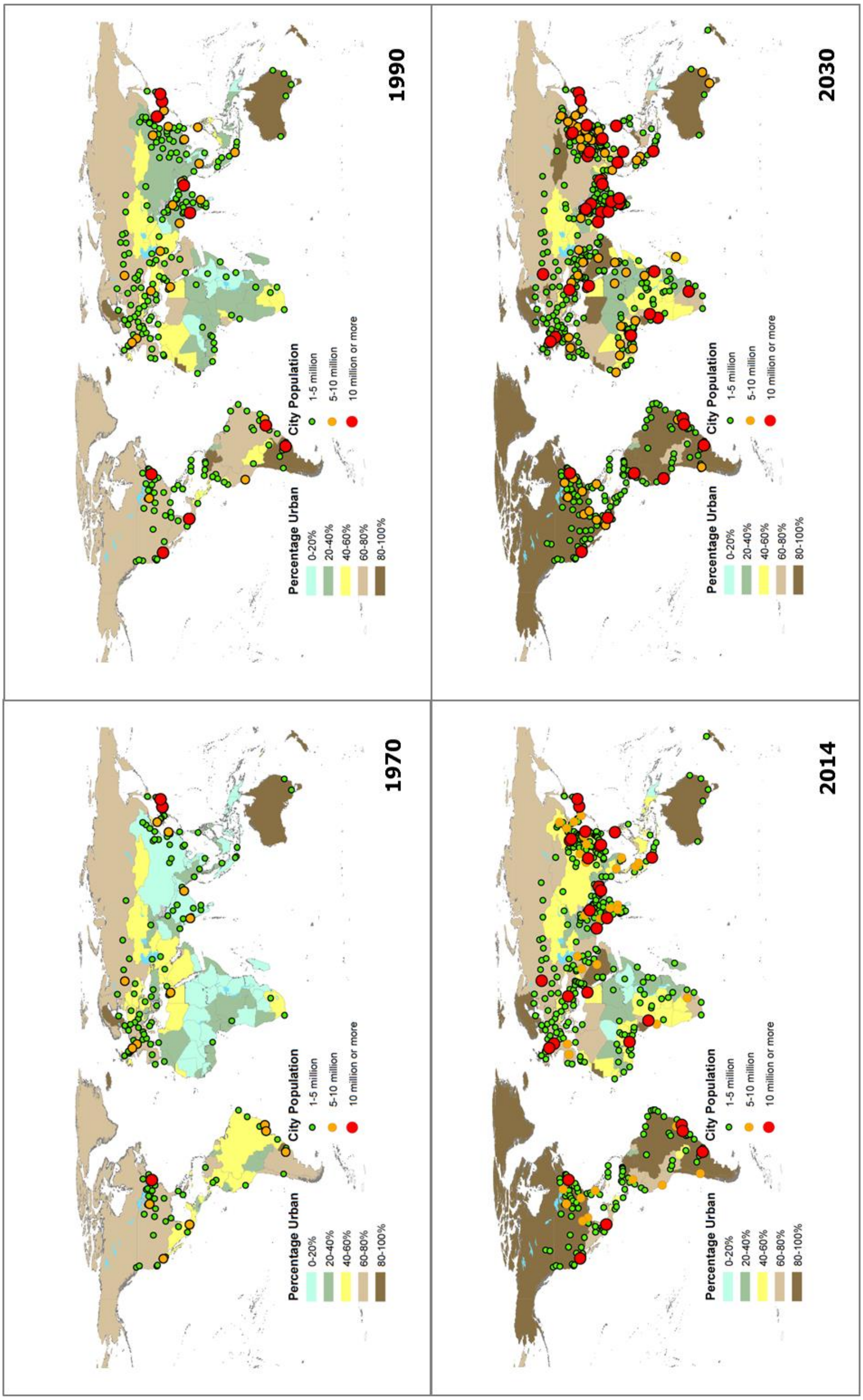
ZHOU, W.,HUANG, G., TROY, A. & M.L. CADENASSO (2009): Object-based land cover classification of shaded areas in high spatial resolution imagery of urban areas: A comparison study. In: *Remote Sensing of Environment*, vol. 113, pp. 1769-1777.

ZHU, G., BIAN, F. & M. ZHANG (2003): A Flexible Method for Urban Vegetation Cover Measurement Based on remote Sensing Images. In: *Proceedings of ISPRS Workshop 2003 "High Resolution Mapping from Space"*, Hanover, Germany, 8 pp.

Chapter 11

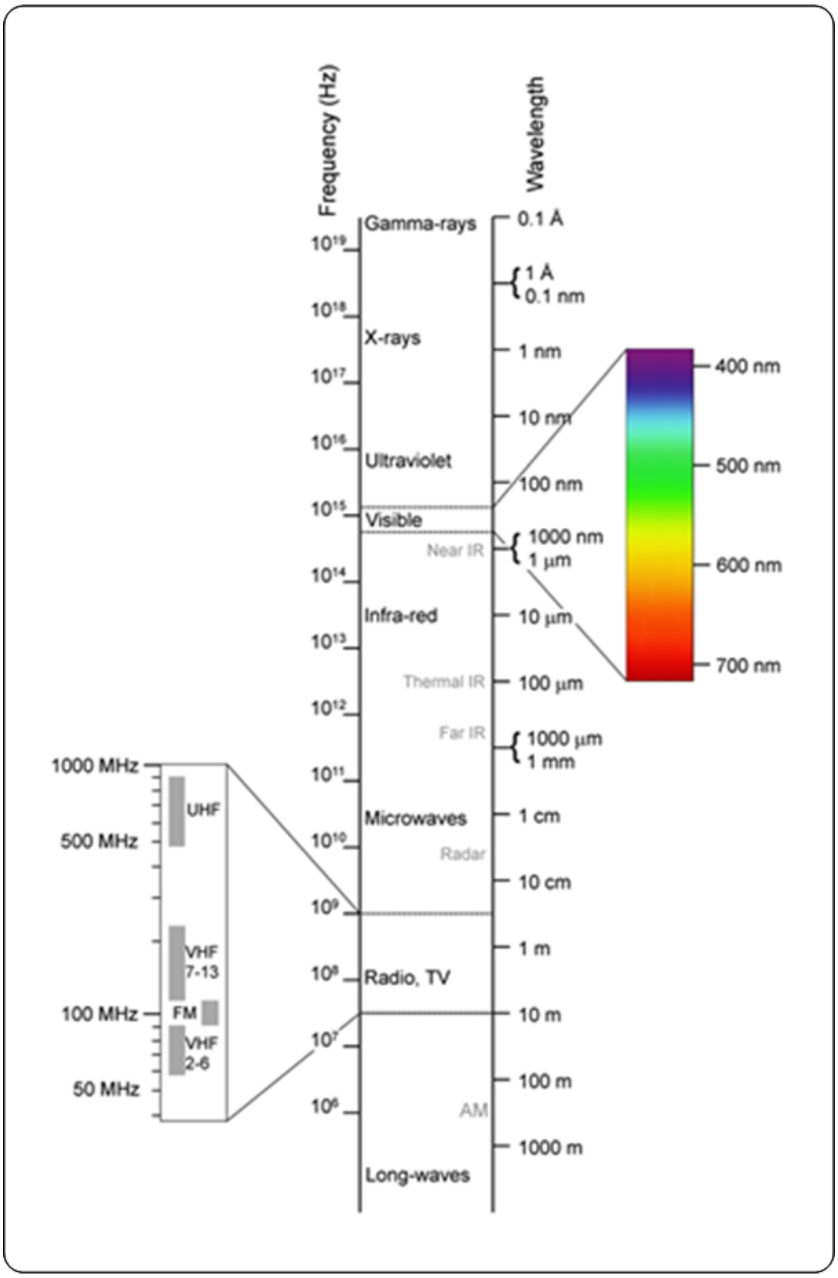
Appendix

A.1: World´s Urbanization Process: Percentage of urban population and location of urban agglomerations 1970 - 2030.



Source: United Nations, World Urbanization Prospects: The 2014 Revision (URL 22).

A.2: Electromagnetic spectrum (EM).



Source: modified after URL 14.

A.3: Metropolitan area of Delhi, India: acquired QuickBird scenes and chosen test sites.

Delhi, India - Acquired QuickBird scene South (S) and chosen test sites

Description of study area South (S)

Delhi's South is a very interesting study area since this municipal area has developed extremely heterogeneously. Hence, this region shows a high degree of fragmentation between planned urban upper class quarters and informal settlements within nearby quarters. The South of Delhi is very disadvantaged in terms of water availability due to depletion and contamination of ground water.

Projection: UTM, Zone: 43 N, Datum & Spheroid: WGS 84

Acquisition date of QuickBird scene: 12/18/2002
Data source: Digital Globe

Cartography & Layout:
Susan Niebergall

A.4: Overview of test site South s3 and detailed view of the settlement types occurring within this area.

Description of test site South s3

The unplanned rapid expansion and the emerging spatial fragmentation results in increasing "social gradients" so that not only the social differences are continuously getting stronger but also the visible contrasts of the urban structure. In test site s3 the following settlement types can be observed:

1 - JJ-colony (very dense urban), 2 - Unauthorized colony (dense urban), 3 - Gated community (medium dense urban).

Further land cover types are: 4 - Vegetation, 5 - Not impervious.

Projection: UTM, Zone: 43 N,
Datum & Spheroid: WGS 84

Acquisition date of the QuickBird scene: 12/18/2002
Data source: Digital Globe

Cartography & Layout: Susan Niebergall

A.5: Test site South s2 and corresponding details of the settlement types occurring within this area.

Description of test site South s2

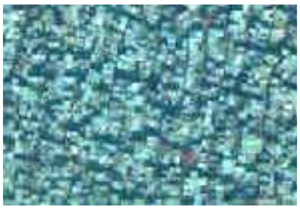
The unplanned rapid expansion and the emerging spatial fragmentation results in increasing "social gradients" so that not only the social differences are continuously getting stronger but also the visible contrasts of the urban structure. In test site s2 the following settlement types can be observed:

1 - JJ-colony (very dense urban), 2 - Unauthorized colony (dense urban), 3 - Resettlement colony (medium dense urban), 4 - Planned unauthorized colony / Farm houses (sparse urban).

Projection: UTM, Zone: 43 N,
Datum & Spheroid: WGS 84
Acquisition date of QuickBird scene: 12/18/2002
Data source: Digital Globe

Cartography & Layout: Susan Niebergall

A.6: Characteristics & description of various settlement types in selected areas in Delhi, India. The description is based on the evaluation of the satellite data and is completed by field photographs.

QuickBird data (4/3/2 composite)	**Description of settlement structures based on visual interpretation of remote sensing data**	**Field photograph**	**Settlement type**
	▪ very small buildings (no clearly identifiable buildings), ▪ very high density/sealing degree (more than 90 percent of roof coverage), ▪ no structure visible, irregular patterns ▪ small shadows, ▪ no or very little vegetation fraction	 *Bhomiheen Camp*	JJ-colony
	▪ small & medium building size, ▪ high density/sealing degree (more than 80 percent of roof coverage), ▪ structure: irregular patterns, ▪ medium large shadows ▪ very little vegetation fraction	 *Tughlakabad Extension*	Unauthorized colony
	▪ mixed building sizes, ▪ dense/high sealing degree, ▪ structure visible, regular patterns, clearly identifiable road network, ▪ mixed shadow size, ▪ little vegetation fraction (partly planned public green space)	 *Trilokpuri*	Resettlement colony
	▪ large building sizes, ▪ medium building density/ sealing degree, ▪ structure visible, grouped buildings, regular patterns, ▪ large shadow size, ▪ medium vegetation fraction	 *Narmada Apartments*	Government quarters

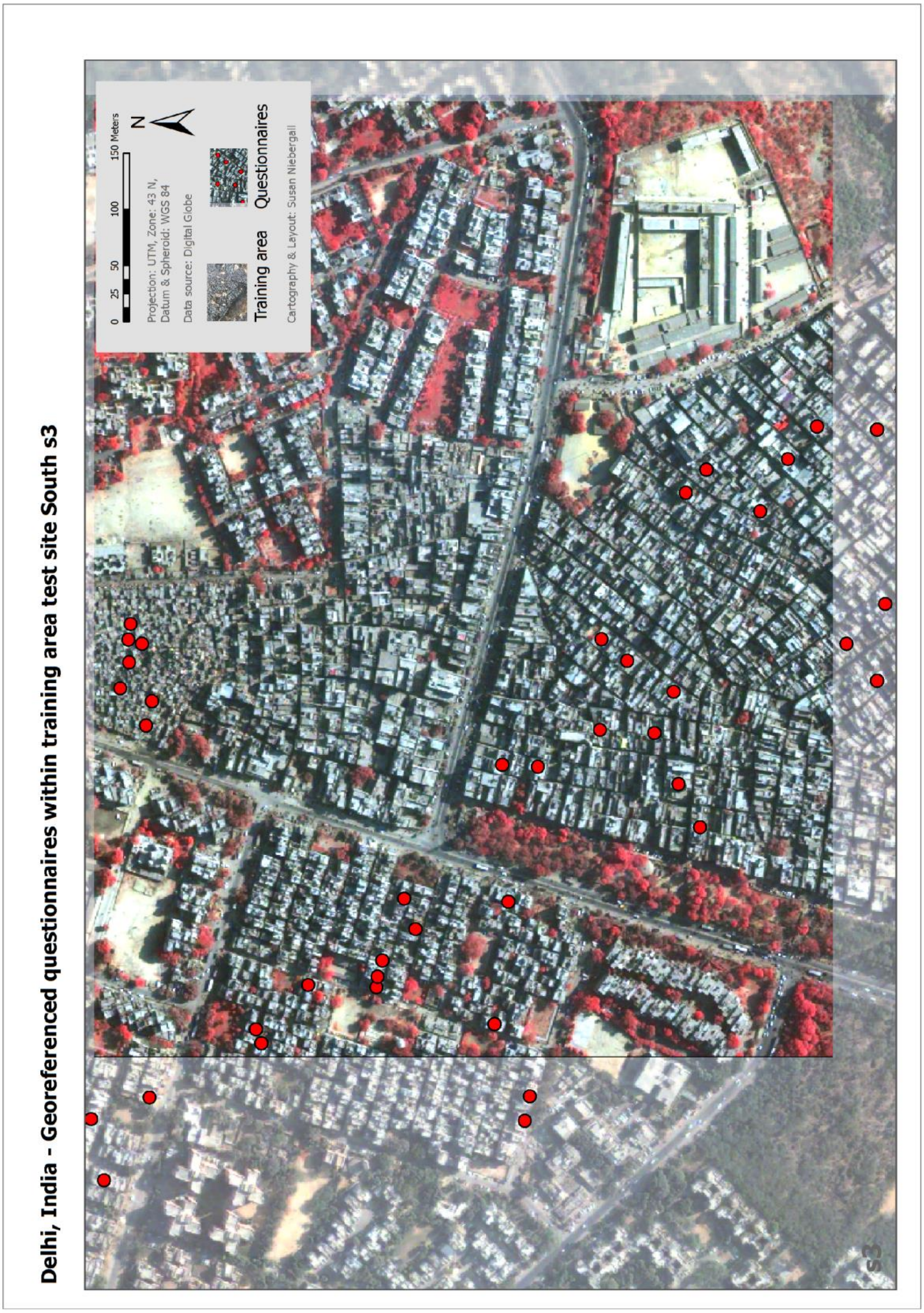
	▪ large building sizes, ▪ medium building density/ sealing degree, ▪ structure visible, grouped buildings, regular patterns, ▪ large shadow size, ▪ medium vegetation fraction	 *Vasundara Enclave*	Gated community
	▪ medium building sizes, ▪ medium building density/ sealing degree, ▪ structure visible, regular patterns ▪ medium shadow size, ▪ medium vegetation fraction (public and private green space)	 *Greater Kailash II*	Gated community
	▪ small buildings, ▪ very high – high density/sealing degree, ▪ no structure visible, irregular patterns, ▪ mixed shadow size, ▪ no or very little vegetation fraction	 *Mehrauli*	Urban village
	▪ medium building sizes, ▪ low building density/ sealing degree, ▪ structure visible, separate buildings, ▪ medium shadow size, ▪ very high vegetation fraction	 *Sainik Farms*	Unauthorized farm houses

(Own draft, Photographs: S. Smollich, October 2005)

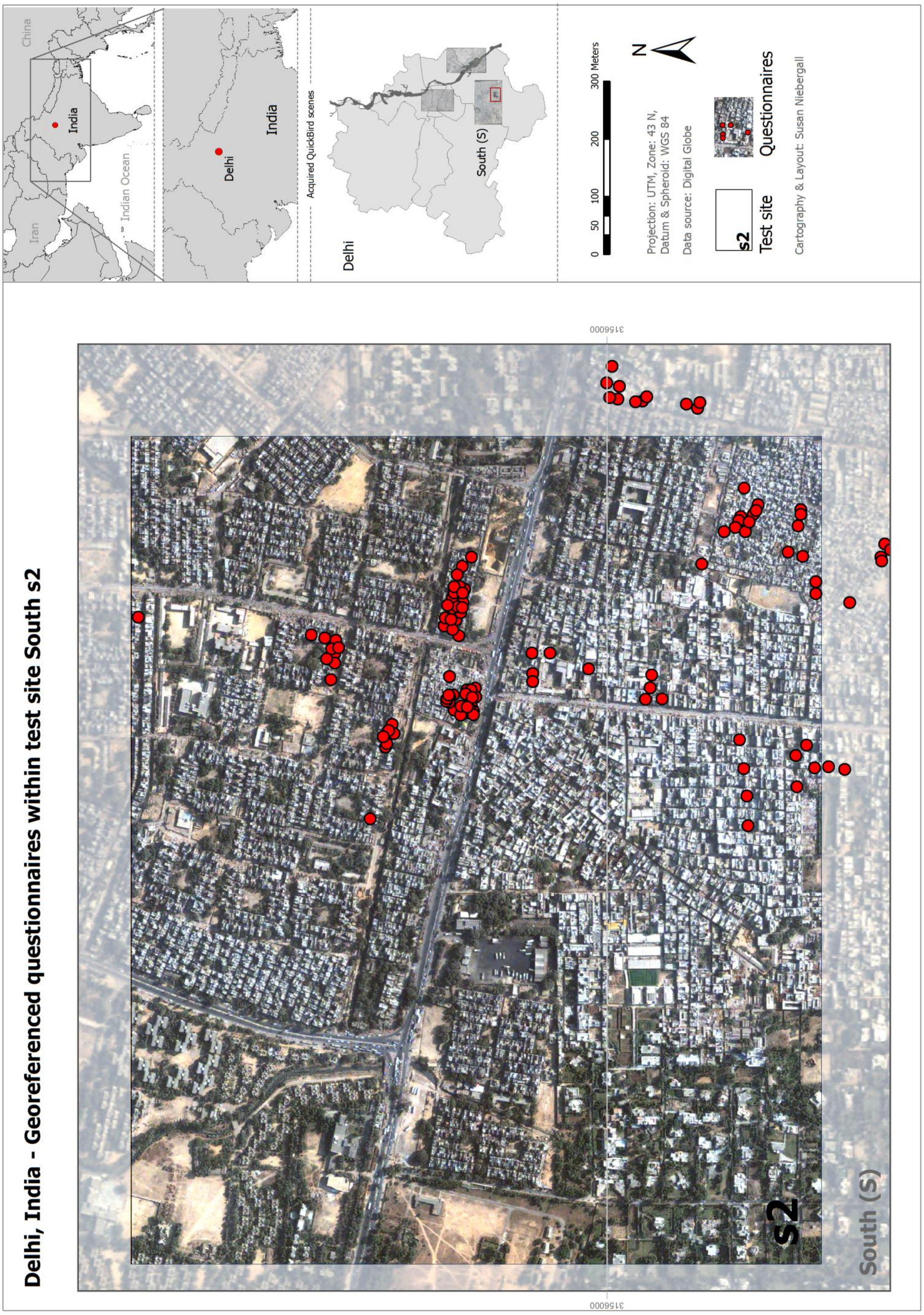
A.7: Georeferenced questionnaires

A.7.1: Georeferenced questionnaires within test site South s3.

A.7.2: Georeferenced questionnaires within the training area of test site South s3.



A.7.3: Georeferenced questionnaires within test site South s2.



A.8: Criteria and corresponding thresholds used in the rule-based classification

A.8.1: Criteria and corresponding threshold values used in the rule-based classification in eCognition^{TM} — identification of very dense urban areas (informal settlements) within QuickBird test site South s3.

Land cover class	Level	Type of criteria	Criteria**	Threshold**
Streets	9	Spectral*	Mean (street layer) Ratio (street layer) Relative border to brighter neighbors (street layer)	<=124 <= 0.01 >= 0.55
Very dense urban	8	Texture	GLCM - Angular Second Moment (all dir.) (3) GLCM - Entropy (all dir.) (3)	<= 0.000123 <= 931.984
Impervious	6	Texture Spectral*	GLCM - Contrast (all dir.) (NDVI) Standard deviation (1)	>= 422.465 <= 981.482
Vegetation	5	Spectral*	Mean (NDVI)	>= 0.145
Shadow	1	Spectral*	Mean difference to neighbors (abs) (NDVI) Mean (3)	>= 0.0327 <= 124

*Layer values

**All criteria (features) and corresponding thresholds were determined using the SEaTH methodology.

A.8.2: Criteria and corresponding threshold values used in the rule-based classification in eCognition^{TM} — identification of sparse urban areas within QuickBird test site South s2.

Land cover class	Level	Type of criteria	Criteria**	Threshold**
Streets	9	Spectral*	Mean (street layer) Ratio (street layer)	<=100 <= 0.01
Sparse urban	9	Spectral*	Ratio to super-object (street layer) Sandard deviation (NDVI) Standard deviation to neighbor pixels (NDVI)	>= 0.9954 >= 0.1373 >= 0.138
Impervious	6	Texture	GLCM - Contrast (all dir.) (NDVI) GLCM - Correlation (all dir.) (NDVI)	>= 477.422 <= 0.9299
Vegetation	5	Spectral*	Mean (NDVI)	>= 0.13
Shadow	1	Spectral*	Mean (4)	<= 126.13

*Layer values

**All criteria (features) and corresponding thresholds were determined using the SEaTH methodology.

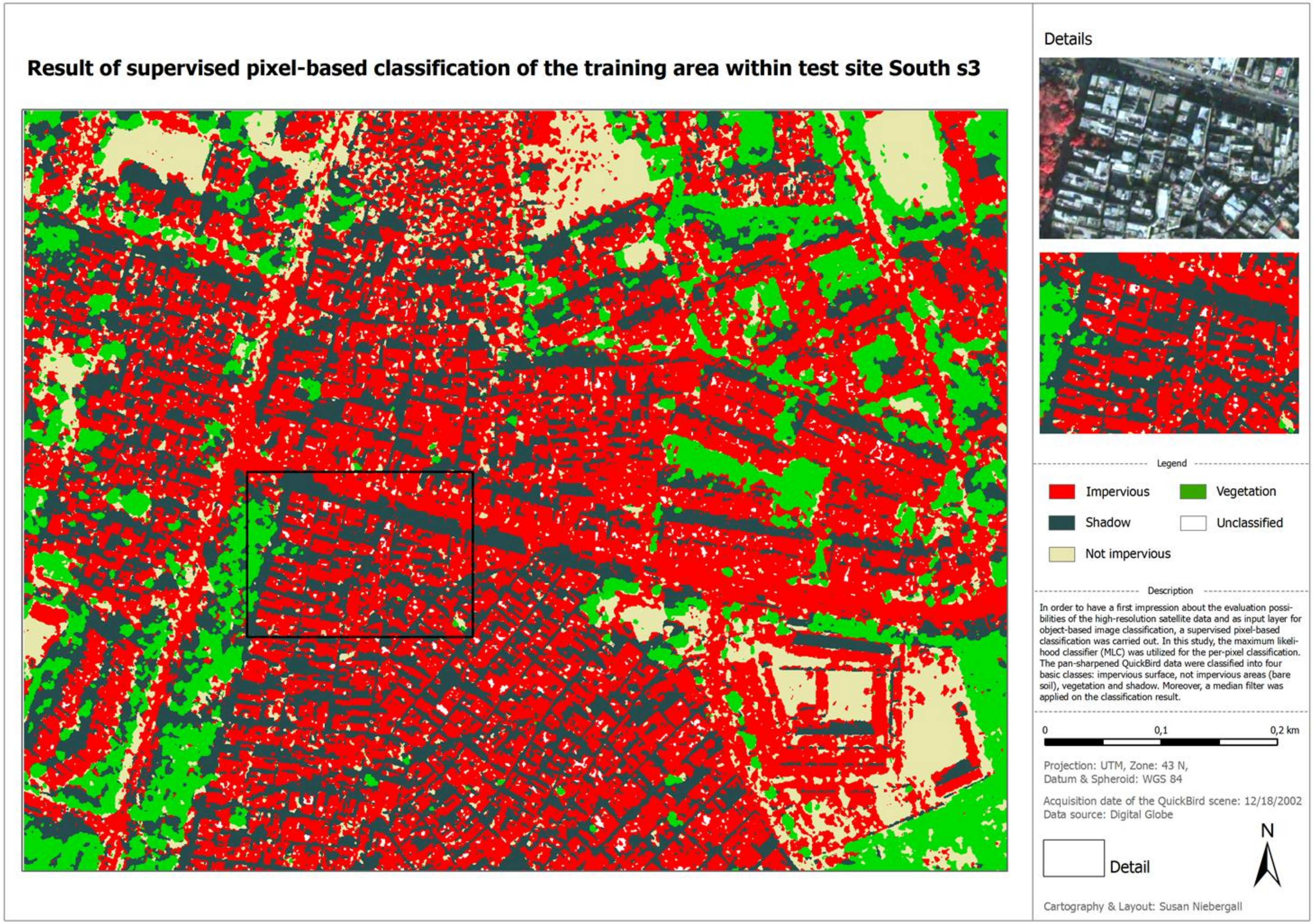
A.8.3: Criteria and corresponding threshold values used in the rule-based classification in eCognition^{TM} — identification of various settlement types within the training area of QuickBird test site South s3.

Land cover class	**Level**	**Type of criteria**	**Criteria****	**Threshold****
Dense urban	8	Spectral*	Ratio (supervised pixel-based classification) Ratio (street layer)	<= 0.1079 >=0.8
Streets	7	Spectral*	Mean (street layer) Ratio (street layer) Relative border to brighter neighbors (street layer)	<=124 <= 0.01 >= 0.55
Medium dense urban	7	Texture	GLCM - Correlation (supervised pixel-based classification)	>= 0.874
		Spectral*	Mean Brightness	>= 23.8768
Very dense urban	7	Texture	GLCM - Angular Second Moment (all dir.) (1) GLCM - Entropy (all dir.) (1)	<= 0.00079 753.335
Vegetation	1	Spectral*	Mean (NDVI) Minimum pixel value (supervised pixel-based classification)	>= 0.02 >= 17
Shadow	1	Spectral*	Mean difference to neighbors (abs) (NDVI) Mean (3)	>= 0.0327 <= 124

*Layer values

**All criteria (features) and corresponding thresholds were determined using the SEaTH methodology.

A.9: Supervised pixel-based classification of the training area within test site s3.



Result of supervised pixel-based classification of the training area within test site South s3

Description

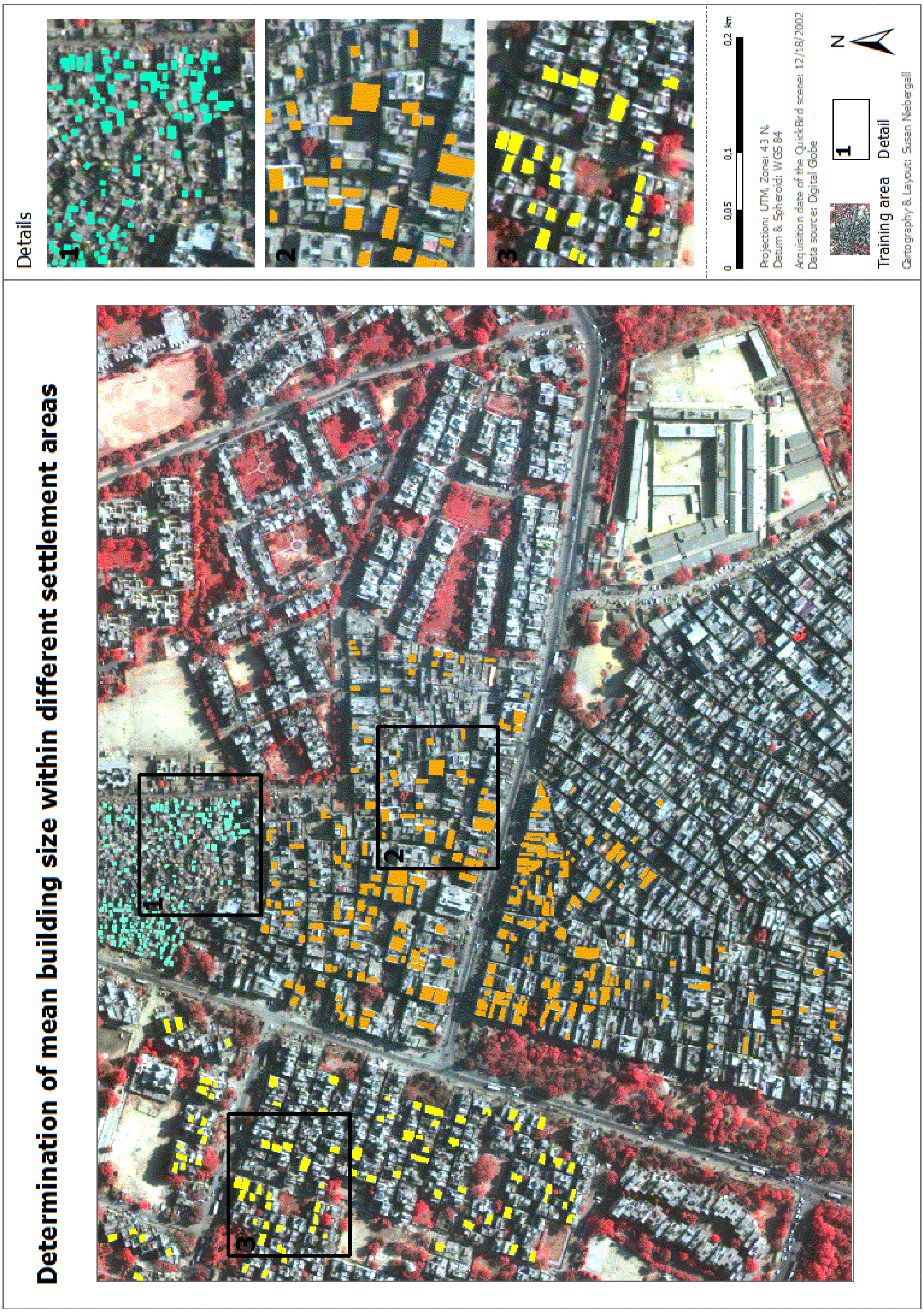
In order to have a first impression about the evaluation possibilities of the high-resolution satellite data and as input layer for object-based image classification, a supervised pixel-based classification was carried out. In this study, the maximum likelihood classifier (MLC) was utilized for the per-pixel classification. The pan-sharpened QuickBird data were classified into four basic classes: impervious surface, not impervious areas (bare soil), vegetation and shadow. Moreover, a median filter was applied on the classification result.

Projection: UTM, Zone: 43 N,
Datum & Spheroid: WGS 84

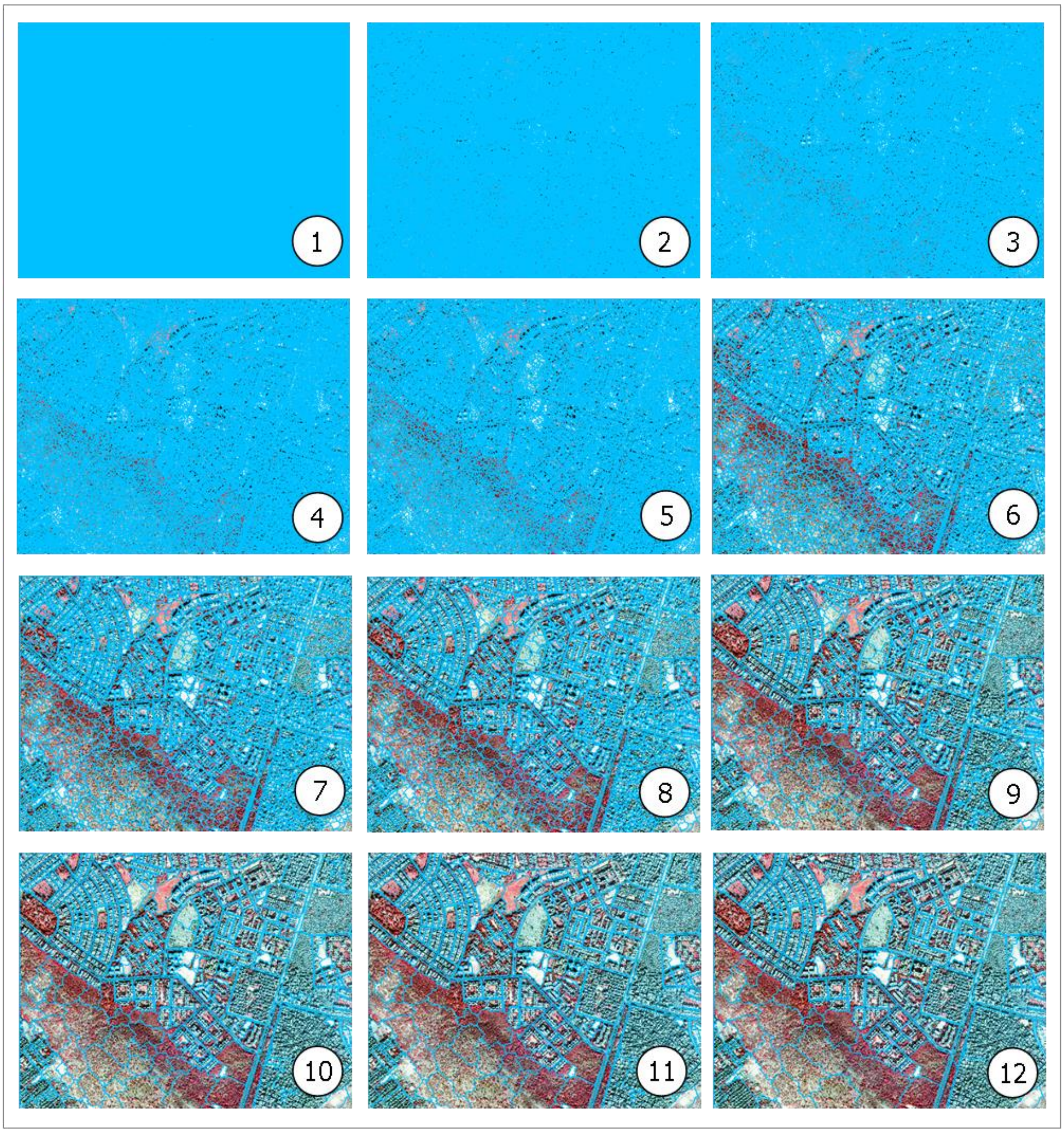
Acquisition date of the QuickBird scene: 12/18/2002
Data source: Digital Globe

Cartography & Layout: Susan Niebergall

A.10: Random mapping of buildings for the determination of the mean building size of different settlement areas (training area within test site s3).

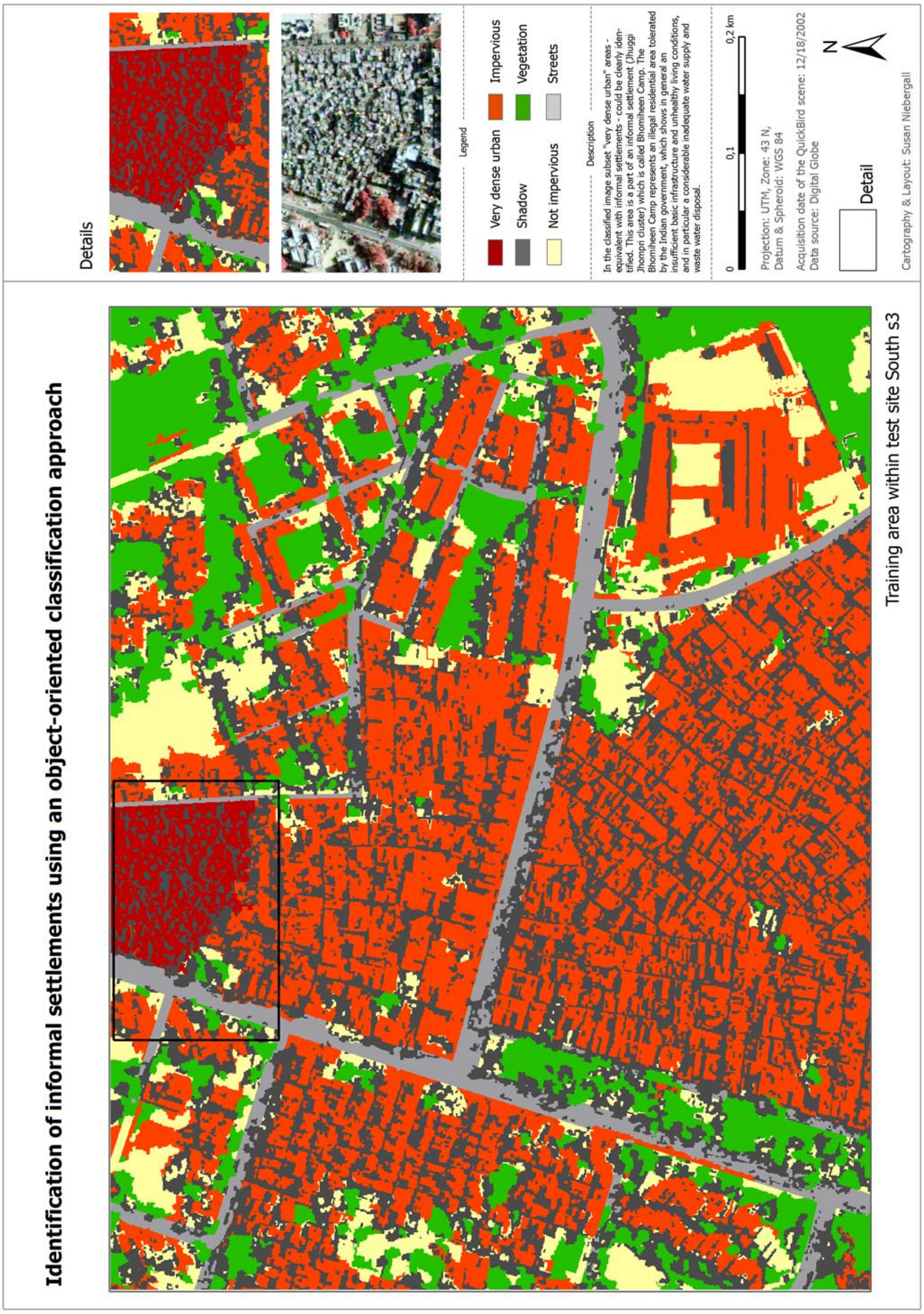


A.11: Results of multi-resolution image segmentation based on the test site South s3. The scale parameter was changed systematically, while the residual homogeneity parameters and the layer weights remained constant (shape [0.5], color [0.5], smoothness [0.3], and compactness [0.7]). The images are numbered according to their segmentation level: 1 — scale 5, 2 — scale 10, …, 12 — scale 200.



A.12: Classification results of the object-oriented approach

A.12.1: Result of object-oriented image classification based on the training area of the fused QuickBird test site South s3 (4, 3, 2) — identification of "very dense urban" areas.



Identification of informal settlements using an object-oriented classification approach

Training area within test site South s3

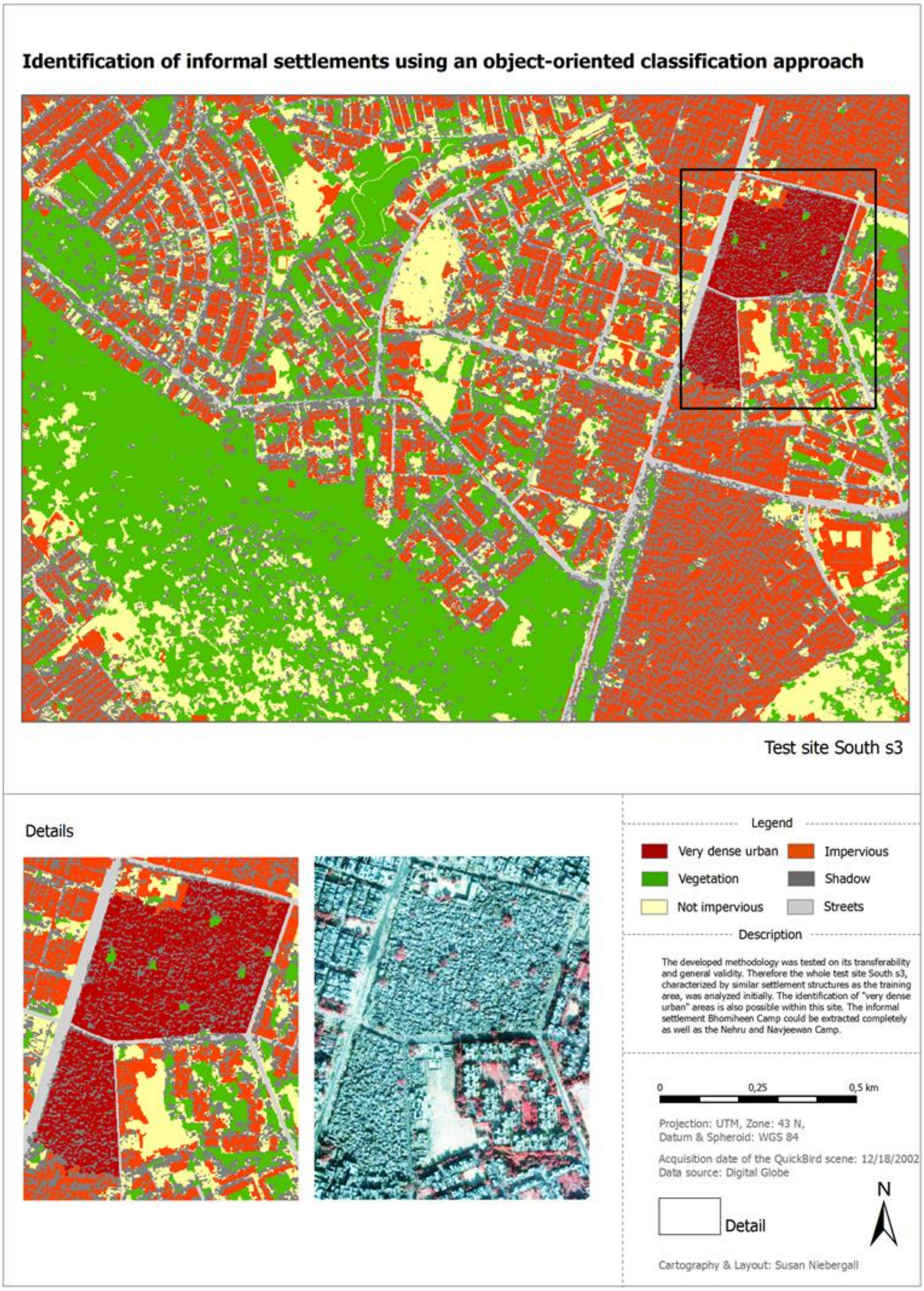
In the classified image subset "very dense urban" areas - equivalent with informal settlements - could be clearly identified. This area is a part of an informal settlement (Jhuggi Jhompri cluster) which is called Bhomiheen Camp. The Bhomiheen Camp represents an illegal residential area tolerated by the Indian government, which shows in general an insufficient basic infrastructure and unhealthy living conditions, and in particular a considerable inadequate water supply and waste water disposal.

Projection: UTM, Zone: 43 N,
Datum & Spheroid: WGS 84

Acquisition date of the QuickBird scene: 12/18/2002
Data source: Digital Globe

Cartography & Layout: Susan Niebergall

A.12.2: Result of object-oriented image classification based on the fused QuickBird test site South s3 (4, 3, 2) — identification of "very dense urban" areas.



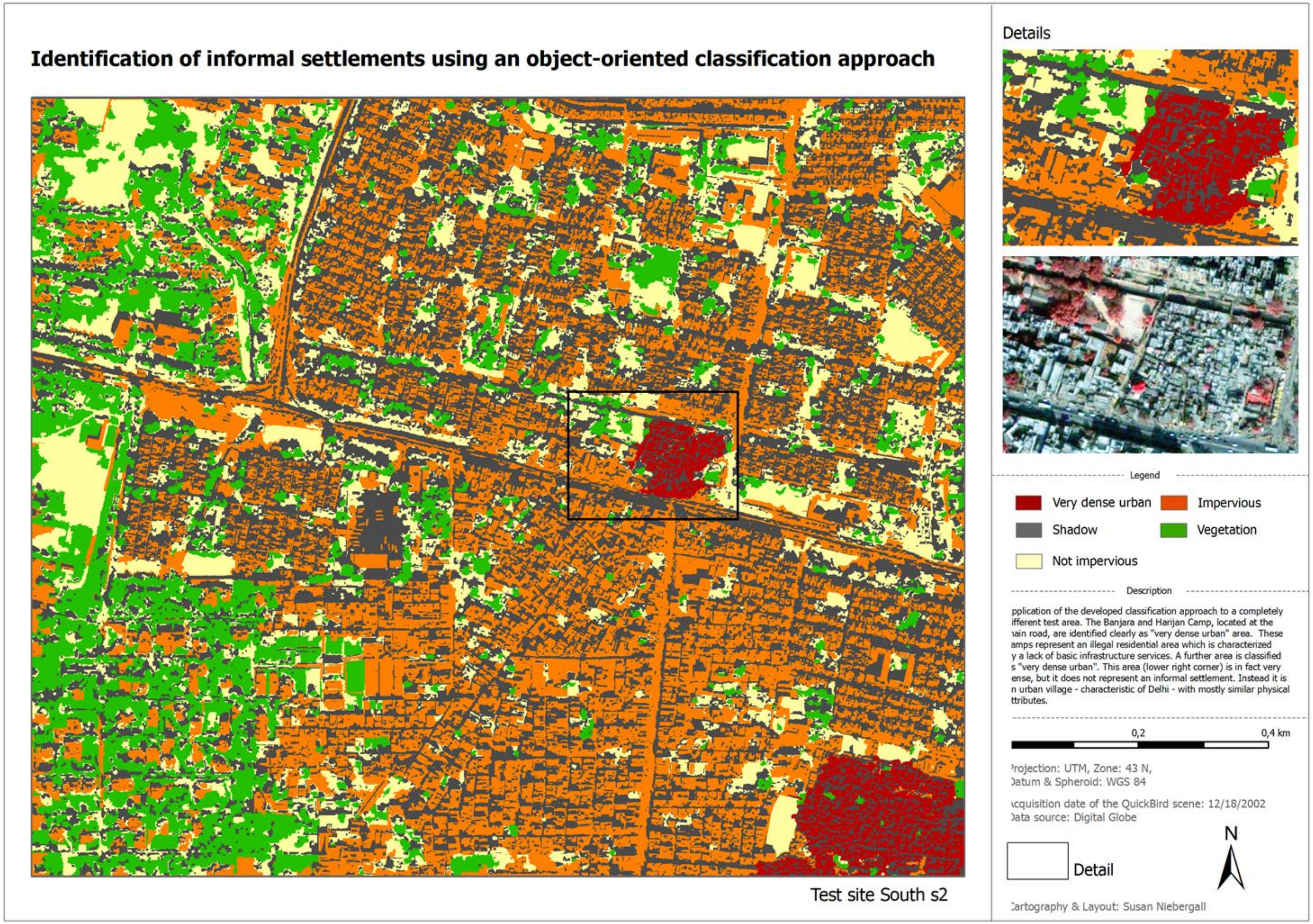
The developed methodology was tested on its transferability and general validity. Therefore the whole test site South s3, characterized by similar settlement structures as the training area, was analyzed initially. The identification of "very dense urban" areas is also possible within this site. The informal settlement Bhomiheen Camp could be extracted completely as well as the Nehru and Navjeewan Camp.

Projection: UTM, Zone: 43 N,
Datum & Spheroid: WGS 84

Acquisition date of the QuickBird scene: 12/18/2002
Data source: Digital Globe

Cartography & Layout: Susan Niebergall

A.12.3: Result of object-oriented image classification based on the fused QuickBird test site South s2 (4, 3, 2) — identification of "very dense urban" areas.



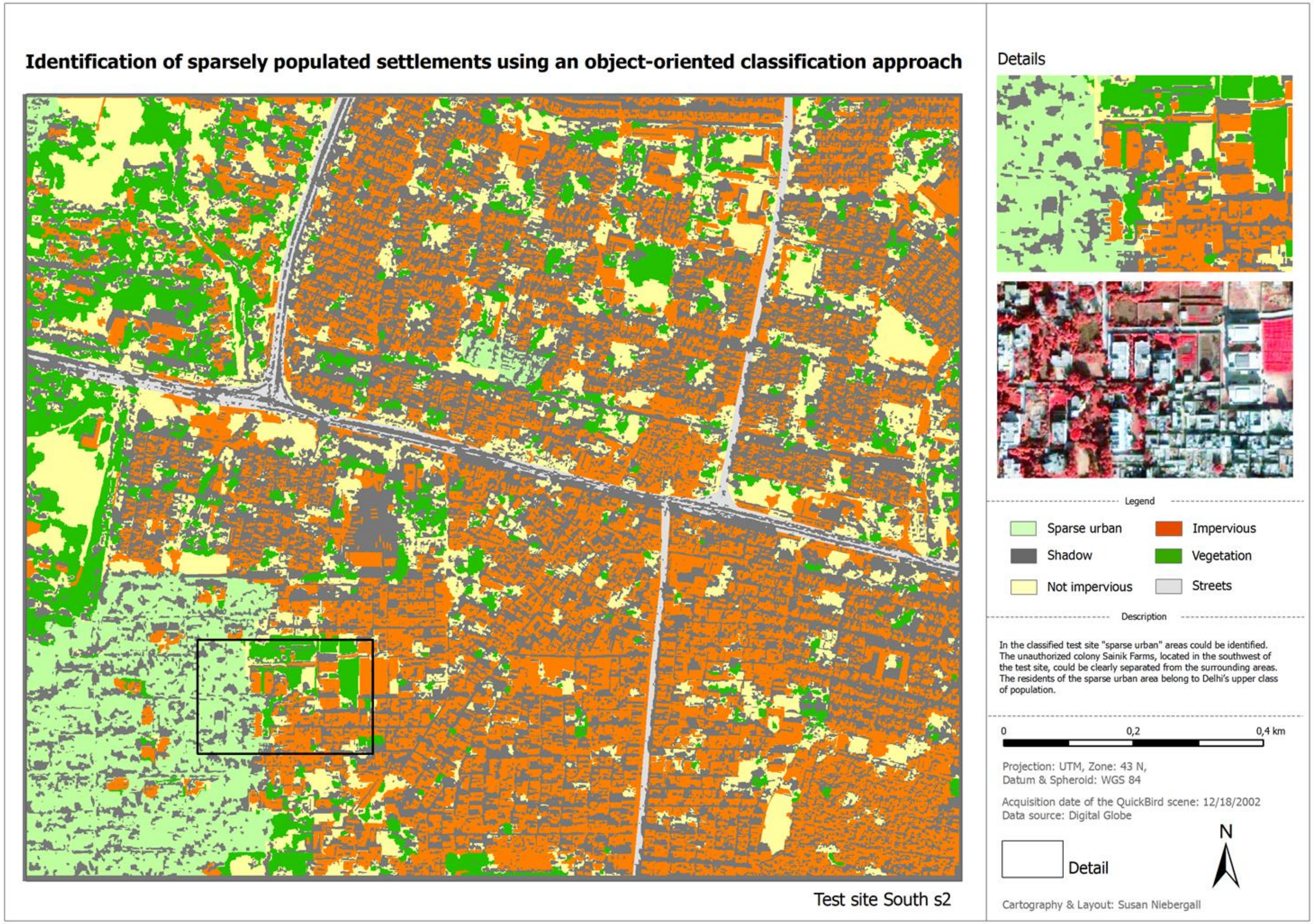
pplication of the developed classification approach to a completely ifferent test area. The Banjara and Harijan Camp, located at the nain road, are identified clearly as "very dense urban" area. These amps represent an illegal residential area which is characterized y a lack of basic infrastructure services. A further area is classified s "very dense urban". This area (lower right corner) is in fact very ense, but it does not represent an informal settlement. Instead it is n urban village - characteristic of Delhi - with mostly similar physical ttributes.

rojection: UTM, Zone: 43 N,
)atum & Spheroid: WGS 84

cquisition date of the QuickBird scene: 12/18/2002
)ata source: Digital Globe

artography & Layout: Susan Niebergall

A.12.4: Result of object-oriented image classification based on the fused QuickBird test site South s2.



In the classified test site "sparse urban" areas could be identified. The unauthorized colony Sainik Farms, located in the southwest of the test site, could be clearly separated from the surrounding areas. The residents of the sparse urban area belong to Delhi's upper class of population.

A.13: Results of image data analysis and integrative analysis

A.13.1: Results of the image data analysis and validation outcomes for selected settlements in the mega city of Delhi.

Name of colony		Settlement Type	Area (A_S) [m²]	Impervious Area (A_I) [m²]	Fraction of impervious area [%]	Average House Size (A_H) [m²]	Number of Houses (N)		
			RS	RS	RS	RS	RS	VC	RS/VC [%]
E	Tughlakabad Extension (subset)	dense urban	116565.48	64975.32	55.74	43	1551	1291	120
F	Tughlakabad Extension (total)	dense urban	328594.32	182700.00	55.6	44	4152	3582	116
G	Kalkaji DDA Flats (subset)	medium dense urban	56037.6	22706.28	40.52	37	614	569	108
H	Kalkaji DDA Flats (total)	medium dense urban	233704.8	88854.48	38.02	41	2167	1986	109

RS - Analysis of Remote Sensing Data, VC - Visual Counting

(Data source: calculated using remotely sensed QuickBird data)

A.13.2: Results of the integrative data analysis for selected settlements in the mega city of Delhi.

Name of colony		Family size (M)*		Total population (P)		Population density (D) [Pop./km²]		Water consumption per capita (W_C) [l/d]*		Total water consumption (W_T) [l/d]		
		As	Q	As	Q	As	Q	As	Q	As	Q	As/Q [%]
E	Tughlakabad Extension (subset)	6.29	6.29	9504.19	9504.19	81535.20	81535.20	72	72	68430168	68430168	100
F	Tughlakabd Extension (total)	6.29	6	26116.08	24912	79478.18	75813.85	72	71	1880357.76	1764752	107
G	Kalkaji DDA Flats (subset)	4.5	4.5	6603.57**	6603.57**	117841.77	117841.77	64	64	422628.48	422628.48	100
H	Kalkaji DDA Flats (total)	4.5	4.44	23306.09**	22995.34**	99724.48	98394.81	64	85	1491589.76	1954603.9	76

As - Assumption, Q - Questionnaire, * Arithmetic Mean, ** calculated with coefficient 2.39 (Ø storeys)

(Data source: calculated using remotely sensed QuickBird data and data from household survey 2005-2006)

A.13.3: Results of the image data analysis and validation outcomes for the upper class settlement *Greater Kailash II* within the mega city of Delhi.

Name of colony		Settlement Type	Area (A_S) [m²]	Impervious Area (A_I) [m²]	Fraction of impervious area [%]	Average House Size (A_H) [m²]	Number of Houses (N)		
			RS	RS	RS	RS	RS	VC	RS/VC [%]
J	Greater Kailash II	medium dense urban	407530.44	119479.68	29.32	103	1159	1043	111

RS - Analysis of Remote Sensing Data, VC - Visual Counting

(Data source: calculated using remotely sensed QuickBird data)

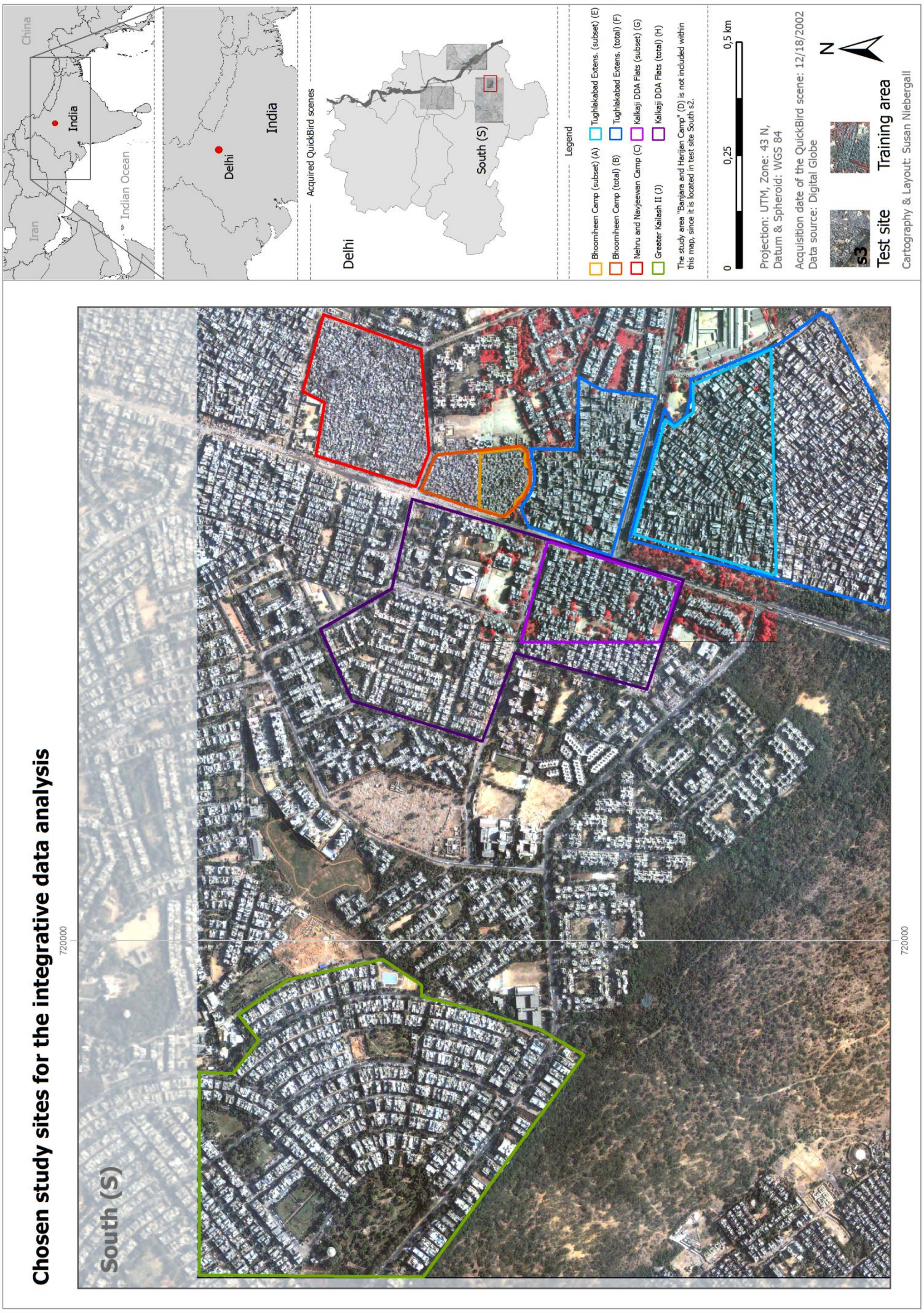
A.13.4: Results of the integrative data analysis for the upper class settlement *Greater Kailash II* within mega city of Delhi.

Name of colony		Family size (M)*	Total population (P)	Population density (D) [Pop./km²]	Water consumption per capita (W_C) [l/d]*	Total water consumption (W_T) [l/d]
		Q	Q	Q	Q	Q
J	Greater Kailash II	4.11	4763	11687.38	146	695398

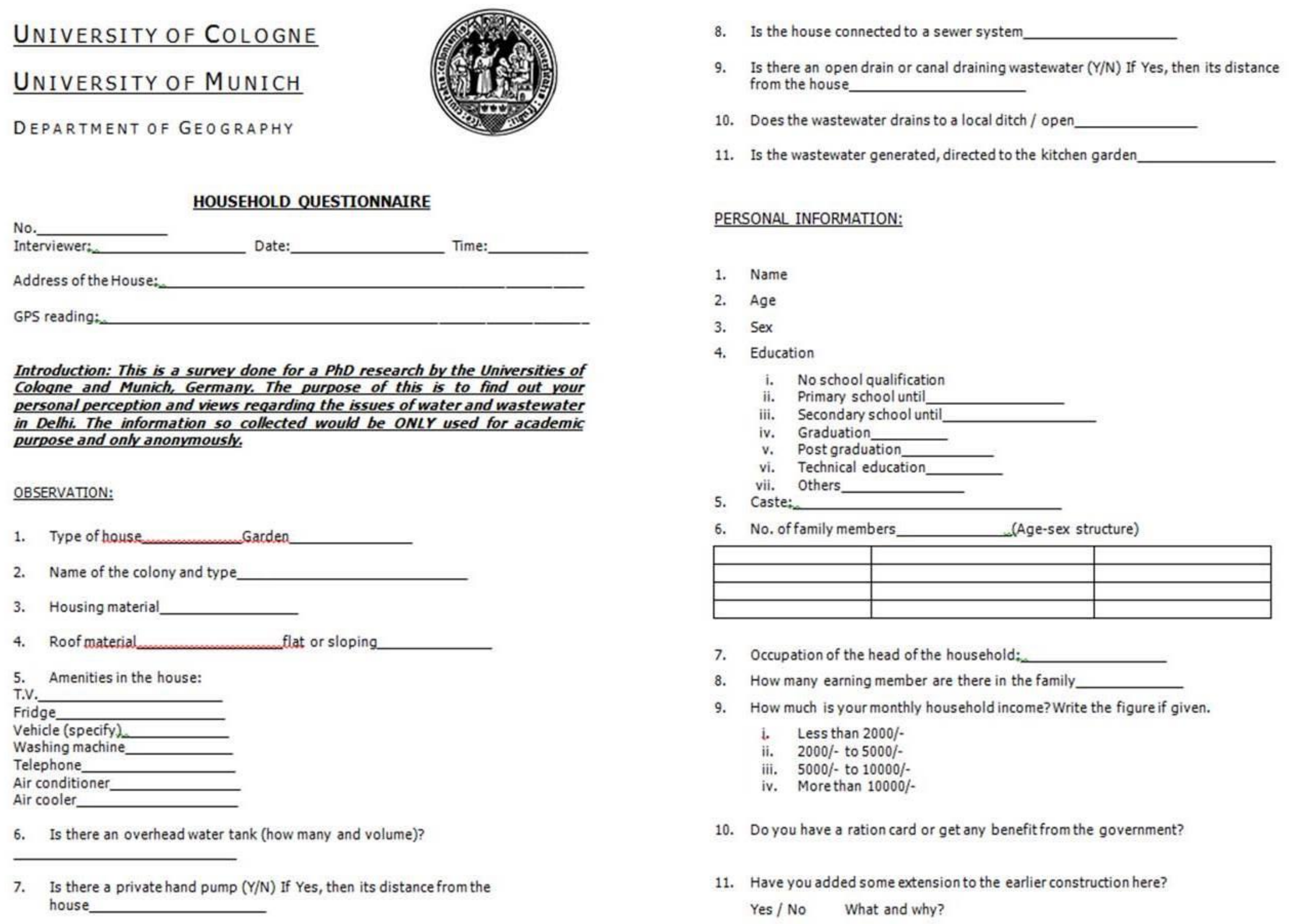
Q - Questionnaire, * Arithmetic Mean

(Data source: calculated using remotely sensed QuickBird data and data from household survey 2005-2006)

A.14: Chosen study sites for the integrative analysis within the mega city of Delhi.



A.15: Questionnaire.



UNIVERSITY OF COLOGNE

UNIVERSITY OF MUNICH

DEPARTMENT OF GEOGRAPHY

HOUSEHOLD QUESTIONNAIRE

No.______________
Interviewer:______________ Date:______________ Time:__________

Address of the House:______________________________________

GPS reading:______________________________________

Introduction: This is a survey done for a PhD research by the Universities of Cologne and Munich, Germany. The purpose of this is to find out your personal perception and views regarding the issues of water and wastewater in Delhi. The information so collected would be ONLY used for academic purpose and only anonymously.

OBSERVATION:

1. Type of house____________Garden____________
2. Name of the colony and type______________________
3. Housing material______________
4. Roof material______________flat or sloping____________
5. Amenities in the house:

T.V.________________
Fridge________________
Vehicle (specify)______________
Washing machine______________
Telephone________________
Air conditioner______________
Air cooler________________

6. Is there an overhead water tank (how many and volume)?

____

7. Is there a private hand pump (Y/N) If Yes, then its distance from the house________________
8. Is the house connected to a sewer system______________
9. Is there an open drain or canal draining wastewater (Y/N) If Yes, then its distance from the house________________
10. Does the wastewater drains to a local ditch / open____________
11. Is the wastewater generated, directed to the kitchen garden______________

PERSONAL INFORMATION:

1. Name
2. Age
3. Sex
4. Education
    - i. No school qualification
    - ii. Primary school until______________
    - iii. Secondary school until______________
    - iv. Graduation__________
    - v. Post graduation__________
    - vi. Technical education__________
    - vii. Others____________
5. Caste:________________________
6. No. of family members____________(Age-sex structure)

7. Occupation of the head of the household:______________
8. How many earning member are there in the family____________
9. How much is your monthly household income? Write the figure if given.
    - i. Less than 2000/-
    - ii. 2000/- to 5000/-
    - iii. 5000/- to 10000/-
    - iv. More than 10000/-
10. Do you have a ration card or get any benefit from the government?
11. Have you added some extension to the earlier construction here?

Yes / No What and why?

12. How did you get to know about this place?

13. When did the respondent has moved here? And reason for moving to this place?
    - i. Nearness to family and relative
    - ii. Nearness to place of work
    - iii. In search of employment
    - iv. Cheaper rent
    - v. Others

14. From where have you moved to this place? (mention the place)
    - i. Within NCT of Delhi
    - ii. Some other place outside NCT
    - iii. From the village within NCR
    - iv. Neighboring states Like UP, Rajasthan, Bihar etc.
    - v. Others

WATER AVAILABILITY AND CONSUMPTION

1. What is the source of water at your residence? (multiple answer to be recorded)
    - i. Municipal tap in house
    - ii. Municipal tap in the community
    - iii. Hand pump to extract the groundwater
    - iii. Well
    - iv. Pond
    - v. Water vendors
    - vi. Tankers by DJB
    - vii. Others

2. How much are you charged for the following and do you think it is appropriate?
    - i. Meter bills
    - ii. Tankers
    - iii. Bottled water
    - iv. Others
    - v. Total

3. How long is the pipe (DJB) water supply available in a day?

    Once / Twice / Thrice / Others________________(note the timing)
    - i. Less than 4 hours
    - ii. 4 to 8 hours
    - iii. 8 to 12 hours
    - iv. 12 to 24 hours
    - v. Others

4. Do you think water supply is sufficient with respect to the quantity, pressure, flow?

    Yes / No, Why?

5. Have you taken any measures in your household or in your neighborhood to overcome these problems? If Yes, what?

    If No, then do you intend to take some measures in future? What have been the obstacles until now?

6. If there is a water crisis, then is it......
    - i. Hamper economic activities (How)
    - ii. Hamper household activities (How)
    - iii. Force you to reschedule your activities in order to be available during the municipal supply of water

7. Do you need to fetch water from outside your house, Y/N, (If Yes, then what is.....)
    - i. Distance of the water point________________
    - ii. Time spent to fetch water___________________
    - iii. Associated cost incurred ________________________
    - iv. Number of family members engaged to get water________
    - v. How often___________________________

8. How much water on an average is used for? (No. of buckets)

	Summer	Winter	Monsoon
i. Bathing			
ii. Washing			
iii. Toilet flushing			
iv. Cleaning			
v. Car washing			
vi. Watering lawns and gardens			
vii. Others			

9. If there is insufficient water supply, does it cause conflict?
    - i. Within household
    - ii. In the locality household
    - iii. Public water point

10. Has the quantity/quality of water required at by your household has changed over last 5 years?

i. Increased	i. Improved
ii. Decreased	ii. Deteriorated
iii. Remained constant	iii. No change

Reasons:

WASTEWATER / SEWERAGE WATER

1. Where does the household wastewater drain?

2. Do you face household wastewater disposal problem in your present situation?

3. Where does the toilet water drain?

4. Do you face sewerage disposal problem?
   Yes / No (what kind)

5. Is wastewater disposal a problem in your own house or in the immediate neighborhood or both? If Yes, What kind?

6. Are the drains in your locality well maintained and who maintains it?
   Yes / No

7. How frequently are the drains/nalas in your area cleaned?
   i. Monthly
   ii. Half yearly
   iii. Yearly
   iv. Do not know

8. How frequently does the drain/nalas in the locality get overflowed?
   i. Seasonally, monsoon seasons mainly
   ii. Most of the time
   iii. Rarely

9. Should community be held responsible for dealing with wastewater generated?
   Yes / No

WATER / WASTEWATER RELATED ENVIRONMENTAL AND HEALTH RISKS

1. Has there ever been any kind of water quality problem in water supply?
   Yes / No
   If Yes, the nature of problem?

2. Does the water that is used have some fowl odor / color?
   Yes / No
   If yes then why do you think it is so?

3. Do you always boil the water before consumption? If Yes, then for how long?
   Yes / No

4. Is there some official recommendation from the water authority to boil drinking water?

5. Is there some restriction of using hand pump water for consumption in this area?
   Why do you think it is so?

6. How strongly do you feel affected by the following problem in your area?
   a) The wastewater disposal
      i. Strongly affected
      ii. Moderately affected
      iii. Little affected
      iv. No effect
   b) Foul odor
      i. Strongly affected
      ii. Moderately affected
      iii. Little affected
      iv. No effect
   c) Others, namely: Mosquitoes, flies, rats, cockroaches and why?

	Mosquitoes	Flies	Rats	Cockroaches	Others
Strongly affected					
Moderately affected					
Little affected					
No effect					

Reason:

7. Whom do you hold responsible for the cleanliness of the area?

8. Have you heard about such incident of sewage water leaking into drinking water in your household or your immediate neighborhood?

   Yes/No

   If yes then relate when and how did it happened?

9. Have you noticed any positive or negative effects of the infrastructure development, like waste water disposal or sewerage system in the area?
   i. Positive changes (what kind)________________________
   ii. Negative changes (what kind)_______________________
   iii. No comments_________________________________

10. What kind of problem does the present wastewater disposal system pose?
    i. Foul odor
    ii. Dirty water logging
    iii. Mosquitoes and other insects breeding
    iv. Eyesore
    v. Chocked and overflowing drains
    vi. Others
    vii. No problem

11. Do you or any other member of your family (particularly children) sometime get in physical contact with the wastewater in the open drain, canal or ditches? Yes or No

    If Yes then how?

12. Do children also defecate in the wastewater channels in front of the house? if Yes, Why?

13. Have you or a family member had any health problem during the past 12 months?

Problem	Age	Sex	How long?	Cost (Rs)
Flu like symptoms: 1. Fatigue 2. Fever 3. Shivering (not due to low temperature) 4. Perspiration (not due to physical activity) 5. Joint and muscle aches 6. Trembling limbs				
Respiratory symptoms: 1. Cough 2. Shortness of breath				
Irritation symptoms: 1. Nose irritation 2. Throat irritation 3. Eye irritation 4. Skin irritation 5. Skin rash 6. Other skin problem				
Neurological symptoms: 1. Headache 2. Forgetfulness 3. Dizziness				
Gastrointestinal symptoms: 1. Lack of appetite 2. Vomiting 3. Diarrhea				
Diseases: (has any of these been diagnosed by a doctor) 1. Cholera 2. Dysentery 3. Malaria 4. Dengue 5. Jaundice/hepatitis 6. Typhoid 7. Hookworm 8. Filariasis				
Others:				

14. Has there been any death in the family in last 1 year_____________Age________Sex______

    Reason for death________________________

PERCEPTION REGARDING WATER / WASTEWATER

1. Do you know of recent activities from NGOs, RWAs, CBOs, DJB and others to improve water supply in your neighborhood? Give examples. Do you benefit from them? (Y/N) Why?

2. How would you rate the present wastewater disposal system in your area?
    - i. Very good
    - ii. Good
    - iii. Poor
    - iv. Non existent
    - v. Cannot say
3. Where do you think the wastewater/sewer finally drains to?
4. Does it receive some kind of treatment?
5. Do you think the present way of wastewater disposal in your community is safe or it has some adverse effect on the environment? How?
6. Why do you think wastewater/sewer disposal is at all a problem in your area?
7. Were you aware of such sanitation problem before settling in this area?
    Yes/No
8. Are you aware that the sewage water is also reused?
9. Is wastewater being reused for agricultural purpose in your area?
10. What are the probable wastewater reuse options in your view?
    - i. Washing vehicles
    - ii. Watering plants
    - iii. Flushing toilets
    - iv. Agricultural purposes
    - v. Others
11. Do you also adapt to some of these alternatives? Specify which one?
12. If the government announces some plan for reusing reclaimed wastewater what would be your reaction?
13. Do you think the concept of community participation is practical in your area for encouraging community based wastewater management techniques?
    Yes / No (Why)
14. Who do you think should take the initiatives of managing the wastewater in your area?
    - i. Individuals at household levels
    - ii. Local committees
    - iii. Government

<u>RESPONSES</u>

1. Are you satisfied with the water supply situation?
    Y/N
    If not, why and whom do you think is responsible?
2. Do you think wastewater and sewerage is managed properly in your area?
    Yes/No, If No, why?
3. Whom do you approach if you face some problem with drainage?
4. Are you aware of health risks from wastewater lying in the open? What do you do regarding it?
5. Do you think reuse of reclaimed wastewater can be a means to cope with wastewater disposal problems?
6. What are your suggestions to cope with
    - i. Water shortage problems?
    - ii. Waste water / sewerage problems?