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OBJECT-BASED INTERPRETATION METHODS FOR MAPPING BUILT-UP AREAS

by

Leena Matikainen

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Abstract

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Abstract

There is a growing demand for high-quality spatial data and for efficient methods of updating spatial databases. In the present study, automated object-based interpretation methods were developed and tested for coarse land use mapping, detailed land cover and building mapping, and change detection of buildings. Various modern remotely sensed datasets were used in the study. An automatic classification tree method was applied to building detection and land cover classification to automate the development of classification rules. A combination of a permanent land cover classification test field and the classification tree method was suggested and tested to allow rapid analysis and comparison of new datasets.

The classification and change detection results were compared with up-to-date map data or reference points to evaluate their quality. The combined use of airborne laser scanner data and digital aerial imagery gave promising results considering topographic mapping. In automated building detection using laser scanner and aerial image data, 96% of all buildings larger than 60 m^2 were correctly detected. This accuracy level (96%) is compatible with operational quality requirements. In automated change detection, about 80% of all reference buildings were correctly classified. The overall accuracy of a land cover classification into *buildings*, *trees*, *vegetated ground* and *non-vegetated ground* using laser scanner and aerial image data was 97% compared with reference points. When aerial image data alone were used, the accuracy was 74%. A comparison between first pulse and last pulse laser scanner data in building detection was also carried out. The comparison showed that the use of last pulse data instead of first pulse data can improve the building detection results. The results yielded by automated interpretation methods could be helpful in the manual updating process of a topographic database. The results could also be used as the basis for further automated processing steps to delineate and reconstruct objects.

The synthetic aperture radar (SAR) and optical satellite image data used in the study have their main potential in land cover monitoring applications. The coarse land use classification of a multitemporal interferometric SAR dataset into *built-up areas*, *forests* and *open areas* lead to an overall accuracy of 97% when compared with reference points. This dataset also appeared to be promising for classifying built-up areas into subclasses according to building density.

Important topics for further research include more advanced interpretation methods, new and multitemporal datasets, optimal combinations of the datasets, and wider sets of objects and classes. From the practical point of view, work is needed in fitting automated interpretation methods in operational mapping processes and in further testing of the methods.

Keywords mapping, updating, change detection, automation, segmentation, classification, object-based, classification tree, building, land cover, land use, urban, topographic database, laser scanning, aerial image, satellite image, SAR

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Tiivistelmä

Laadukkaan paikkatiedon tarve kasvaa jatkuvasti, ja paikkatietokantojen ajantasaistukseen tarvitaan tehokkaita menetelmiä. Tässä tutkimuksessa käytettiin useita uudenaikaisia kaukokartoitusaineistoja. Niiden pohjalta kehitettiin ja testattiin automaattisia, objektipohjaisia tulkintamenetelmiä yleispiirteiseen maankäytön luokitteluun, yksityiskohtaiseen maanpeitteen ja rakennusten kartoitukseen sekä rakennusten muutostulkintaan. Rakennusten tulkintaan ja maanpeiteluokitteluun sovellettiin automaattista luokittelupuumenetelmää, jonka avulla voidaan automatisoida luokittelusääntöjen kehittäminen. Uusia aineistoja voidaan analysoida ja vertailla nopeasti, kun luokittelupuumenetelmää käytetään yhdessä pysyvän maanpeiteluokittelutestikentän kanssa.

Luokittelu- ja muutostulkintatuloksia verrattiin niiden laadun arvioimiseksi ajantasaiseen kartta-aineistoon tai referenssipisteisiin. Ilmalaserkeilausaineisto ja digitaalinen ilmakuva-aineisto yhdessä antoivat lupaavia tuloksia maastotietojen kartoitusta ajatellen. Automaattisessa rakennusten tulkinnassa 96 % kaikista yli 60 m^2:n rakennuksista tunnistettiin oikein. Tämä tarkkuustaso (96 %) vastaa käytännön laatuvaatimuksia. Automaattisessa muutostulkinnassa noin 80 % kaikista referenssirakennuksista luokiteltiin oikein. Maanpeiteluokittelussa neljään luokkaan saavutettiin laserkeilaus- ja ilmakuva-aineistoa käyttäen 97 %:n kokonaistarkkuus referenssipisteisiin verrattuna. Pelkkää ilmakuva-aineistoa käytettäessä tarkkuus oli 74 %. Tutkimuksessa verrattiin myös ensimmäiseen ja viimeiseen paluupulssiin perustuvia laserkeilausaineistoja rakennusten tulkinnassa. Vertailu osoitti, että viimeisen paluupulssin käyttö ensimmäisen sijasta voi parantaa tulkintatuloksia. Automaattisten tulkintamenetelmien tuloksista voisi olla hyötyä maastotietojen manuaalisessa ajantasaistusprosessissa tai lähtötietoina kohteiden automaattisessa rajauksessa ja mallinnuksessa.

Tutkimuksessa käytettyjen synteettisen apertuurin tutkan (SAR) tuottamien kuvien ja optisen satelliittikuvan tärkeimmät hyödyntämismahdollisuudet liittyvät maanpeitteen kartoitukseen. Yleispiirteisessä maankäyttöluokittelussa kolmeen luokkaan saavutettiin moniaikaista interferometrista SAR-aineistoa käyttäen 97 %:n kokonaistarkkuus referenssipisteisiin verrattuna. Aineisto osoittautui lupaavaksi myös rakennettujen alueiden jatkoluokitteluun rakennustiheyden perusteella.

Jatkotutkimusten kannalta tärkeitä aiheita ovat edistyneemmät tulkintamenetelmät, uudet ja moniaikaiset aineistot, eri aineistojen optimaalinen yhdistäminen sekä useampien kohteiden ja luokkien tarkastelu. Käytännön näkökulmasta työtä tarvitaan automaattisten tulkintamenetelmien sovittamiseksi operatiivisiin kartoitusprosesseihin. Myös menetelmien testausta on jatkettava.

Avainsanat kartoitus, karttojen ajantasaistus, muutostulkinta, automaatio, segmentointi, luokittelu, objektipohjainen, luokittelupuu, rakennus, maanpeite, maankäyttö, rakennettu alue, maastotietokanta, laserkeilaus, ilmakuva, satelliittikuva, SAR

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PREFACE

The study presented in this thesis was carried out as part of my work as a researcher at the Finnish Geodetic Institute (FGI), Department of Remote Sensing and Photogrammetry. I hope that this collection of work could provide useful information and be a source of motivation for further development and testing of automated interpretation methods in various mapping tasks. Certainly, there are still many problems to solve, but I believe that there is also much potential in such methods when applied to state-of-the-art remotely sensed datasets.

I am thankful to everyone who has helped me in the study. First of all, I would like to thank Professor Juha Hyyppä from the FGI for his valuable advice, encouraging attitude, and indispensable support for my work. The opportunity to work with new and interesting datasets and with automated interpretation methods for mapping applications made this thesis possible. However, my main personal objective has not been to present a doctoral thesis, and therefore I am also grateful for the possibility to concentrate on research and see the thesis as a possible future option rather than a necessary outcome of my work. My first advisor at the FGI was Professor Risto Kuittinen. I am thankful to him for the good guidance I received from him in the early years of my career. My interest in object-based interpretation methods and map updating dates back to the mid 1990s when I began to study satellite image segmentation under Professor Kuittinen's guidance. Later, it has been very interesting to see the emergence of new and better datasets, to follow the increasing popularity of object-based image analysis methods, and to continue to work with these topics. I would also like to thank the supervisor of the thesis, Professor Henrik Haggrén from Aalto University, Department of Real Estate, Planning and Geoinformatics, for his valuable advice concerning both this thesis and my previous studies.

Several other persons have also contributed to the study, and I would like to express my gratitude to all of them. The co-authors of the appended papers Harri Kaartinen, Kirsi Karila, Eero Ahokas, Lauri Markelin, Marcus Engdahl, and Hannu Hyyppä have had important roles in the study. Mika Karjalainen also participated in the preprocessing of several datasets used in the study, and Eija Honkavaara contributed to the acquisition of digital aerial images. The staff of our department and of the entire FGI have helped me in many ways during the work. It has been a pleasure to work with you all. I also appreciate our various common sports activities, which have been a source of much delight to me. I would like to thank the pre-examiners of the thesis, Professor Yifang Ban from KTH Royal Institute of Technology, Stockholm, Sweden, and Professor George Vosselman from the University of Twente, Enschede, The Netherlands, for their valuable comments. The anonymous reviewers of the appended papers also provided useful comments on the study.

During the past years, I participated in some projects that were not part of the thesis work, but that were related to the same topics, and were thus useful for the study. Two projects on the applications of laser scanning at the National Land Survey of Finland (NLS) increased my understanding on the challenges of operational, nationwide mapping. I would like to thank Juha Kareinen and other project members for good cooperation in those projects. It was also interesting to participate in a EuroSDR (European Spatial Data Research) project comparing change detection methods for buildings. I would like to thank Nicolas Champion from IGN (Institut Géographique National), France, for organizing the project and Xinlian Liang from the FGI for his contribution in testing our building detection method.

Data for the study described in the thesis have been obtained from several organizations, including the European Space Agency (ESA), DLR (German Aerospace Center) and Astrium GmbH (ProSmart II), TopoSys GmbH, Blom Kartta Oy (previously FM-Kartta

Oy), the NLS, and the City of Espoo. Financial support for the study has been obtained from the Academy of Finland and Tekes (the Finnish Funding Agency for Technology and Innovation). I extend my thanks to these organizations for their support.

Finally, special thanks are reserved to my parents, sister, brother, niece, nephews, and friends for their support and for the many happy days that have served to counterbalance the demands of my daily work.

Kirkkonummi, 13 August 2012
Leena Matikainen

CONTENTS

LIST OF PUBLICATIONS

The thesis is based on the following publications, referred to in the text by their Roman numerals:

I Matikainen, L., Hyyppä, J., Engdahl, M.E., 2006. Mapping built-up areas from multitemporal interferometric SAR images – A segment-based approach. *Photogrammetric Engineering and Remote Sensing*, 72(6): 701-714.

II Matikainen, L., Hyyppä, J., Hyyppä, H., 2003. Automatic detection of buildings from laser scanner data for map updating. Proceedings of the ISPRS Working Group III/3 Workshop: 3-D Reconstruction from Airborne Laserscanner and InSAR Data, Dresden, Germany, 8–10 October 2003. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. XXXIV, Part 3/W13, pp. 218-224.

III Matikainen, L., Hyyppä, J., Kaartinen, H., 2009. Comparison between first pulse and last pulse laser scanner data in the automatic detection of buildings. *Photogrammetric Engineering and Remote Sensing*, 75(2): 133-146.

IV Matikainen, L., 2006. Improving automation in rule-based interpretation of remotely sensed data by using classification trees. *The Photogrammetric Journal of Finland*, 20(1): 5-20.

V Matikainen, L., Hyyppä, J., Ahokas, E., Markelin, L., Kaartinen, H., 2010. Automatic detection of buildings and changes in buildings for updating of maps. *Remote Sensing*, 2(5): 1217-1248.

VI Matikainen, L., Karila, K., 2011. Segment-based land cover mapping of a suburban area – Comparison of high-resolution remotely sensed datasets using classification trees and test field points. *Remote Sensing*, 3(8): 1777-1804.

II is a peer-reviewed conference article. Other publications are peer-reviewed journal articles.

The author's contribution

In **I**, I carried out the tests and analyses, wrote the paper (with contributions from the co-authors in describing the SAR dataset), and I had the main responsibility for planning and developing the methods. Juha Hyyppä was the advisor in the study and participated in the planning of the methods. Marcus Engdahl was responsible for creating the interferometric SAR dataset, i.e., interferometric processing, geocoding and other SAR image preprocessing operations, and for the collection of the reference points.

In **II**, I carried out the tests and analyses and had the main responsibility for planning and developing the methods and writing the paper. Juha Hyyppä was the advisor in the study and participated in the planning of the methods. Hannu Hyyppä created a digital terrain model and wrote part of Section 2.2.

In **III**, I carried out the tests and analyses, wrote the paper, and had the main responsibility for planning the study. Juha Hyyppä was the advisor in the study and participated in the planning. Harri Kaartinen ortho-rectified the aerial images, created the ortho image mosaic, and participated in the preprocessing of the map data.

I had the sole responsibility for Paper **IV**.

In **V**, I carried out the tests and analyses, wrote the paper, and had the main responsibility for planning and developing the methods. Juha Hyyppä was the advisor in the study and participated in the planning of the methods. Eero Ahokas participated in the preprocessing of the laser scanner data, Lauri Markelin ortho-rectified the aerial images and created the ortho image mosaic, and Harri Kaartinen participated in the preprocessing of the map data.

In **VI**, I developed the method and had the main responsibility for planning the study and writing the paper. I carried out the tests and analyses related to aerial image and laser scanner data (classification tests 1 and 2). Kirsi Karila carried out the tests and analyses related to optical satellite image and SAR data (classification tests 3–5). She participated in the planning of the study and in the writing of the paper (especially the parts related to classification tests 3–5).

LIST OF ABBREVIATIONS

ALTM	Airborne Laser Terrain Mapper
AO	Announcement of Opportunity
CAD	Computer-aided design
CORINE	Coordination of Information on the Environment
DEM	Digital elevation model
DLR	Deutsches Zentrum für Luft- und Raumfahrt (German Aerospace Center)
DMC	Digital Mapping Camera
DSM	Digital surface model
DTM	Digital terrain model
EEA	European Environment Agency
ERS	European Remote Sensing Satellite
ESA	European Space Agency
EuroSDR	European Spatial Data Research
GEOBIA	Geographic object-based image analysis
GIS	Geographic information system
GIScience	Geographic information science
GLCM	Grey level co-occurrence matrix
L band	Band in SAR data; wavelength 23 cm
LHH	L band; horizontal transmit, horizontal receive
LHV	L band; horizontal transmit, vertical receive
LVV	L band; vertical transmit, vertical receive
MATLAB	Matrix laboratory
nDSM	Normalized digital surface model
NDVI	Normalized difference vegetation index
NIR	Near-infrared
NLS	National Land Survey of Finland
NN	Nearest neighbour
OBIA	Object-based image analysis
SAR	Synthetic aperture radar
SPOT	Satellite Pour l'Observation de la Terre
TM	Thematic Mapper
X band	Band in SAR data; wavelength 3 cm
XHH	X band; horizontal transmit, horizontal receive
XVV	X band; vertical transmit, vertical receive
1-n/n-1	Class in the change detection results: One building in the old or new dataset corresponds to more than one in the other
2D	2-dimensional
3D	3-dimensional

1. INTRODUCTION

1.1 Background and motivation

Maps and other types of spatial data are used increasingly in modern-day societies. Maps and image-based visualisations on the Internet (e.g., Google, 2012; Microsoft, 2012) have rapidly achieved great popularity, and navigation applications have become part of people's everyday life. Various tasks in the fields of administration, planning, construction, transportation, and natural resources management, to name a few, rely on accurate geographic datasets. There is also growing interest being shown in more detailed data, such as 3D city models and virtual reality representations (see, for example, Leberl et al., 2009; Haala and Kada, 2010; Siegert, 2011). The development of applications is supported by the rapid development of data acquisition technology relying on satellite, airborne, and terrestrial mobile mapping sensors.

Spatial data are stored in digital databases. The most extensive and accurate nationwide datasets are maintained by national mapping agencies, among them the National Land Survey of Finland (NLS), and they include topographic data, such as the Topographic Database in Finland, which includes the details of the terrain and built-up environment in vector format. The positional accuracy of the data matches map scales of 1:5000–1:10 000. The most important features presented in the database include transportation networks, buildings, land use, water bodies, elevation, administrative boundaries, and nomenclature. The database is used as source material in map production, and it can also be used in various other applications, such as navigation, route finding, planning, and environmental monitoring. (Maanmittauslaitos, 2005, 2012.) The production process of the Topographic Database in 1992–2001 was based on digital photogrammetry, field checking, and digitizing of existing maps (Jakobsson, 2006).

The updating of the Topographic Database at the NLS is a continuous process utilizing clues and data obtained from sources such as municipalities. In addition to this, regular updating of the database is carried out at intervals of 3–10 years in each region, depending on the updating need. These updates mainly rely on aerial images. They include improvement of elevation data and updating of objects (features) in the database. When updating objects, use is made of stereo images and ortho images. The objective is to check all objects in the area and to carry out the necessary corrections. This work is carried out by human interpreters, and it is based on visual comparison between the new images and the database overlaid on the images. The corrections can be related to the geometry or the attributes of the objects. The most important objects to update include roads, buildings, fields, water bodies, and transmission lines. Finally, field checks are carried out to complete the work. (Kareinen, 2008; Maanmittauslaitos, 2011.)

In addition to detailed topographic data, spatial datasets with coarser spatial resolution are collected. One example is the European-wide CORINE (Coordination of Information on the Environment) land cover classification with a mapping scale of 1:100 000 and a minimum mapping unit of 25 hectares. CORINE land cover classifications have been updated regularly and they match specific reference years. Changes between two consecutive reference years are also provided as products. In this case, the minimum mapping unit is 5 hectares. (EEA, 2007.) Törmä et al. (2011) describe the production of the Finnish CORINE land cover 2006 classification, which was based on the combination of automated satellite image classifications and national geographic datasets. One of the datasets used in the production was the Topographic Database. Visual interpretation was also needed for some classes.

Given the growing demand for high-quality spatial data, efficient updating of databases becomes a matter of central importance. In particular, urban areas are subject to frequent change and thus they are also very important areas for mapping and updating of map databases. This applies to Finland and other developed countries with accurate spatial databases and high demand for up-to-date and even more detailed information. On the other hand, the same also applies to less developed parts of the world with different mapping challenges. Currently about 50% of the world's population live in cities. By 2030, the percentage is expected to increase to 75%, and the largest cities will be located in developing countries. (Ulkoasiainministeriö, 2011.)

As described above, typical updating of topographic mapping is still mainly based on visual and manual work. Mapping organizations, however, are showing high interest in developing automated tools to assist in the updating process (e.g., Petzold and Walter, 1999; Eidenbenz et al., 2000; Armenakis et al., 2003; Knudsen and Olsen, 2003; Busch et al., 2004; Steinnocher and Kressler, 2006; Champion, 2007; Holland et al., 2008). The development of fully automated processes does not seem realistic in the near future, but the use of semi-automated updating workflows is considered to be a promising approach to increasing the automation level and efficiency of the work. For example, the results of automated change detection could be provided for human operators, who could then concentrate on updating objects that probably need changes, rather than having to check all of the objects in the area.

As regards remotely sensed datasets used in mapping, significant development has taken place in recent years. Multispectral imagery from digital airborne sensors has replaced aerial film-based photography, and airborne laser scanning has become an operational technique enabling the acquisition of accurate height data. In Finland, the laser scanning of the entire country was launched in 2008. The primary use for laser scanner data is in the production of digital elevation models (DEMs) (Vilhomaa and Laaksonen, 2011), but the data also have a lot of potential for other applications, including the updating of the Topographic Database (Kareinen, 2008). In addition to aerial systems, increasingly detailed data are obtained from satellites. Several high-resolution optical and synthetic aperture radar (SAR) satellite systems with the potential for mapping tasks have been launched during the past few years (Karjalainen, 2010; Jacobsen, 2011). The new data acquisition techniques provide interesting possibilities for developing useful automated tools, both for detailed topographic mapping and coarser land use and land cover monitoring applications. Accurate height data produced by laser scanning are particularly useful when mapping elevated objects such as buildings (e.g., Hug, 1997). Multispectral aerial imagery helps to distinguish various objects and land cover classes. Optical and SAR satellite images enable, for example, the monitoring of urbanization in different parts of the world (Taubenböck et al., 2012). Special techniques such as SAR interferometry can also provide promising datasets for automated classifications (e.g., Engdahl and Hyyppä, 2003).

There are different tasks that can be distinguished in the visual interpretation work done by a human interpreter. Campbell (2002) divides these into classification, enumeration, measurement, and delineation. Classification is defined as "the assignment of objects, features, or areas to classes based on their appearance on the imagery". It can include detection (determination of the presence or absence of a feature), recognition (assignment to a general class or category), and identification (assignment to a very specific class). Enumeration is the listing or counting of discrete items. Measurement can include measurement of distances, heights, volumes, and areas (the subject of photogrammetry), and quantitative assessment of image brightness (photometry or radiometry). Delineation corresponds to the outlining of regions. (Campbell, 2002.) The same basic tasks should be considered when automating mapping work. In the research focusing on automated methods, the term “extraction” is often used in this connection. For example, Brenner (2010) defines building extraction as “the process to detect, structure, geometrically reconstruct and attribute building outlines and 3D models of buildings”. He discusses building extraction research from laser scanner data under the headings “Building detection”, “Outlining of footprints”, and “Building reconstruction” (related to 3D modelling). Using the above terminology, the present study is mainly concerned with classification and detection. As a special type of classification and detection, change detection, which is an essential step in the updating of databases, is also studied.

In the field of automated classification of remotely sensed data, a common trend during the past decade has been the increasing popularity of object-based image analysis methods (Blaschke, 2010). The basic principle of carrying out image segmentation and classifying homogeneous objects instead of single pixels is not a new one (see Kettig and Landgrebe, 1976), but such methods have gained greater popularity following the introduction of commercial software and new high-resolution datasets. Object-based methods allow the use of various object characteristics in the interpretation process, including mean values, texture, size, shape, and contextual relationships. The use of this type of information can make automated approaches more alike to the visual analysis done by human interpreters, and this has long been considered to be important (see, for example, Tailor et al., 1986). The development of good interpretation rules on the basis of human knowledge can, however, be a laborious task. Therefore, automated methods for creating classification rules for object-based interpretation are of interest (e.g., Hodgson et al., 2003; Thomas et al., 2003).

1.2 Hypothesis

The basic hypothesis in this study was that highly automated classification and change detection methods can be developed for mapping and map updating by applying object-based interpretation approaches and new remotely sensed datasets, and that these methods can produce results of high quality.

1.3 Objectives of the study

The objectives of the study were as follows:

- To develop automated, object-based interpretation methods for mapping built-up areas, including:
  - Coarse land use mapping: detection of built-up areas as entities and distinguishing different types of built-up areas.
  - Detailed land cover and building mapping: detection of individual buildings and other land cover classes.
  - Change detection of buildings.
- To test the quality of these methods.

All of the study areas included built-up areas. At the level of individual objects, the study focused on buildings. Different levels of detail from coarse land use mapping to the detection of changes in individual buildings were included in the analysis.

Coarse land use mapping was investigated by using a multitemporal interferometric SAR dataset. Detailed land cover and building mapping was mainly developed by using airborne laser scanner and aerial image data, but high-resolution airborne SAR data and optical satellite image data were also used in land cover classification tests. Change detection of buildings was developed based on laser scanner and aerial image data, and an existing building map.

1.4 Structure and contribution of the study

The study consists of a summary and six original publications. Following this introductory section, Section 2 presents a literature review describing previous research on the topics of the study. The materials and basic methods used in the study are presented in Section 3. Section 4 summarizes the results achieved, including the methods developed for mapping built-up areas and the test results of the methods. The results, their potential applicability for practical mapping applications, and needs for further research are discussed in Section 5. Section 6 provides the summary and the conclusions of the study.

Regarding the objectives of the study, the contribution of the original publications can be summarized as follows:

- Paper **I** discussed **coarse land use mapping**. A segment-based method was applied to mapping built-up areas by using a multitemporal interferometric SAR dataset. As far the author knows, this approach was different from those used in previous land use classification studies with similar datasets. The study also provided new information on the feasibility of a multitemporal interferometric SAR dataset for distinguishing different types of built-up areas.
- Paper **II** presented a basic approach to the automated **detection of buildings and changes in buildings** by using laser scanner data. This was the first published study known to the author that described automated change detection between a building map and a new laser scanner dataset for the purpose of updating maps. The paper also included both pixel-based and object-based numerical quality evaluations of the building detection results, and thus it provided information, which was not widely available at the time of publishing. The basic approach presented in Paper **II** was further developed and tested in later papers.
- Paper **III** compared the **building detection** results obtained by using first pulse and last pulse laser scanner data. Detailed numerical quality analyses were carried out, and this was different from previous studies conducted on the topic. The paper thus provided basic information for further method development and application of laser scanner data for building detection.
- Paper **IV** discussed **building detection and detailed land cover mapping**. The possibility of increasing the automation level of object-based interpretation was tested by applying the classification tree method to building detection using laser scanner data and aerial image data, and to land use mapping using high-resolution SAR data. At the time of publishing, the classification tree method had not been widely applied to the analysis of laser scanner data. The paper also presented the idea of using the combination of permanent land cover classification reference data and the classification tree method for rapid analyses of new datasets.
- Paper **V** presented the finalized **building detection and change detection** methods and a thorough quality analysis of the results. An improved version of the change detection method was developed. In addition to the evaluation of the building detection results, the change detection results were now compared with an extensive reference dataset representing real changes. This type of information was not widely available in previous literature.

- Paper **VI** discussed **detailed land cover mapping**. The permanent test field approach suggested in Paper **IV** was tested in practice by applying it to the comparison of land cover classifications from various datasets: digital aerial image data, digital aerial image data and laser scanner data, high-resolution optical satellite image data, high-resolution SAR data, high-resolution SAR data and laser scanner data. The author is not aware of previous studies comparing the suitability of such datasets for land cover classification in one study area.

2. LITERATURE REVIEW

2.1 General

This literature review presents the background to the foremost methodological approaches applied in the study, i.e. object-based image analysis and classification trees, and it summarizes previous research on the main topics of the individual papers. The review concentrates on topics that are of central significance to the study and belonged to the author's sphere of responsibility. Some additional references can be found in the appended papers.

2.2 Object-based image analysis

The main idea in object-based image analysis is to analyze objects instead of single pixels. The objects to be analyzed are typically obtained from image segmentation, but they can also be derived from map data (e.g., Janssen, 1993; Johnsson, 1994a), or a combination of image segmentation and map data (e.g., Janssen, 1993). Object-based approaches for analyzing remotely sensed data have been developed and investigated since the 1970s, but it is since 2000 that their popularity has significantly increased (Blaschke, 2010). Some authors have even considered object-based image analysis as a new sub-discipline of geographic information science (GIScience) (Hay and Castilla, 2008). Important reasons for the growing interest in object-based methods include the increasing availability of high-resolution datasets and commercial software packages. The first software package was eCognition in 2000, and it has had an important role in the development. (Blaschke, 2010.) Over the years, object-based or other similar approaches have been referred to by different names, such as "segment-based", "object-oriented", "parcel-based", or "region-based" methods. The acronyms OBIA (object-based image analysis) and GEOBIA (geographic object-based image analysis) are commonly used in the newest literature. The meanings of the terms may vary slightly depending on authors (see, for example, Baatz et al., 2008, for a discussion on object-based and object-oriented approaches, and Hay and Castilla, 2008, for a formal definition of GEOBIA). The term "object-based" (e.g., Blaschke et al., 2008) is used in this thesis.

It has often been mentioned that object-based approaches resemble visual interpretation and provide connections between image analysis and geographic information systems (GIS). These topics were already considered important in earlier research (see, for example, Tailor et al., 1986; Ehlers et al., 1989; Argialas and Harlow, 1990; Wilkinson, 1996; Baltsavias and Hahn, 2000; Heipke et al., 2000), and they have been highlighted as important characteristics of object-based image analysis in the newest literature (e.g., Benz et al., 2004; Hay and Castilla, 2008; Blaschke, 2010). An important benefit of object-based methods is the possibility to exploit diverse object characteristics in the interpretation process, including, for example, mean values, texture, shape, and contextual relationships. The importance of such attributes increases with data from the modern, high-resolution remote sensing sensors where objects of interest include several pixels (see, for example, Argialas and Harlow, 1990; Hoffmann and Van der Vegt, 2001; Blaschke, 2010). Even if many different object attributes are not applicable, one can expect classification based on spectral data to be more reliable when it is based on the mean values of homogeneous regions instead of on single pixel values (see, for example, Dean and Smith, 2003). The ideal object-based (or object-oriented) analysis workflow has been presented as being an iterative process, where segmentation and classification stages can alternate until the objects corresponding to the desired objects of interest are obtained (Benz et al., 2004;

Baatz et al., 2008). Another typical characteristic of object-based methods is multiscale analysis, which can exploit different hierarchical levels of segmentations (Benz et al., 2004). Older examples of iterative workflows and multiscale segmentation methods can also be found. Tailor et al. (1986) discussed the relationships between segmentation and interpretation in earlier literature, and Freuder (1976), Beaulieu and Goldberg (1989) and Woodcock and Harward (1992) presented hierarchical segmentation methods.

The benefits of object-based image interpretation approaches have been investigated in numerous studies. Kettig and Landgrebe (1976) found that the extraction of homogeneous objects before classification improved the accuracy of aerial and satellite image classification results. Moreover, the classification results were less noisy and closer to the desired output form than pixel-based results. Object-based methods were applied in the 1990s, for example, in the thesis works of Janssen (1993) and Johnsson (1994a). According to Johnsson (1994a), the primary advantage of region-based analysis methods was that the regions represented meaningful units of analysis in terms of application. In our earlier studies (Matikainen et al., 2002; Matikainen, 2005), region-based approaches were applied in different case studies and they proved to be useful. For example, the use of segmentation as a preprocessing step increased the accuracy of satellite image classifications. A literature review showed that several other studies have also reported on the benefits of region-based methods (Matikainen, 2005). On the other hand, some disadvantages related to segmentation have also been reported; one such disadvantage being that segmentation generalizes objects (Koch et al., 2003). Blaschke (2010) presents an extensive review on recent literature discussing the use of object-based methods in different application areas.

An important part of typical object-based image analysis methods is segmentation, which is a process of subdividing an image into its constituent regions or objects (Gonzalez and Woods, 2002). By 1990, hundreds of segmentation algorithms had already been presented in the literature (Argialas and Harlow, 1990). A review of segmentation methods has been presented, for example, by Pal and Pal (1993). In our studies discussed in this thesis, we used the multiresolution segmentation method (Baatz and Schäpe, 2000) of the eCognition software. This is a region-based segmentation method based on bottom-up region merging and a local optimization process minimizing the growth of a given heterogeneity criterion. A heterogeneity criterion is defined as a combination of spectral (colour) and spatial heterogeneity. Spatial heterogeneity is based on the compactness and smoothness of the segments. The segmentation of a digital surface model (DSM) derived from laser scanner data is shown in Figure 1 as an example. A heterogeneity criterion based completely on colour information, which in this case corresponded to height, was used for segmentation of DSMs.

Object-based image analysis methods are often rule-based or knowledge-based approaches relying on classification rules developed by human experts (e.g., Benz et al., 2004; Lang, 2008). The basic ideas of knowledge-based interpretation have been discussed, for example, by Tailor et al. (1986), Richards and Jia (1999), and Jensen (2005). Rule-based approaches are flexible methods and allow using various different remotely sensed and ancillary datasets, object attributes and human expertise in the interpretation process. Rules can be formulated, for example, by using fuzzy membership functions (e.g., Tso and Mather, 2001; Benz et al., 2004) or the Dempster-Shafer theory of evidence (e.g., Tso and Mather, 2001) to deal with uncertainty. The fuzzy set theory and the Dempster-Shafer theory were presented by Zadeh (1965) and Shafer (1976), respectively. Common problems with knowledge-based methods are that the development of the rules is time consuming and that new datasets or changes in the characteristics of the datasets require changes in the rules.

Figure 1. Segmentation of a DSM derived from laser scanner data (from **II**).

2.3 Classification trees

The idea of classification trees (also called decision trees) is to perform stepwise splitting of the data into classes that are arranged in a hierarchical structure (see, for example, Richards and Jia, 1999; Tso and Mather, 2001). Tree structures are often used in knowledge-based classification approaches. The tree structure, and the classification rules associated with it, can be defined manually, but many automatic approaches have also been presented in the literature (see Safavian and Landgrebe, 1991). Classification tree tools are available in data mining and statistical software packages. In our studies, we used the classification tree tools available in the Statistics Toolbox of the MATLAB software (The MathWorks, 2012). These are based on the classification tree method presented by Breiman et al. (1984).

Classification trees created with various algorithms and tools have been used increasingly in remote sensing studies in recent years. This method is capable of using continuous and categorical data, it does not require assumptions regarding the distribution of the data, and it can be used to create classification rules, i.e., a classification tree, automatically from a large number of input attributes (see, for example, Hansen et al., 1996; Friedl and Brodley, 1997; Lawrence and Wright, 2001; Thomas et al., 2003). The method is, thus, also well suited for use in object-based classification with many different types of object attributes being available. Classification trees are considered easier to use and understand than artificial neural networks, which are another popular non-parametric classification method (see, for example, Hansen et al., 1996; Chan et al., 2001; Pal and Mather, 2003). The tree structure provides information on the roles and importance of different attributes in the classification problem, which can be very useful, from both the practical and the theoretical perspective (Hansen et al., 1996). Compared with more traditional classification methods, such as the maximum likelihood classifier, comparable or better classification results have been reported with the classification tree method (Hansen et al., 1996; Friedl and Brodley, 1997; Huang and Jensen, 1997). In some cases, however, the achieved accuracy can also be lower (Pal and Mather, 2003).

A classification tree contains a root node, non-terminal nodes, and terminal nodes (Figure 2). The root node and each of the non-terminal nodes contain a question that asks whether a given attribute satisfies a given condition. Each question can be answered as

”Yes” or ”No”. The terminal nodes represent individual classes. When an object is classified, the conditions are tested beginning from the root node. From each node, the object goes to the left descendant node if it satisfies the condition and to the right descendant node if it does not satisfy the condition. Finally, the object ends up at one of the terminal nodes and it is assigned to the corresponding class. One class can be represented by several terminal nodes. There can, thus, be several alternative paths, i.e., sequences of questions that lead to the same classification result. (Breiman et al., 1984; The MathWorks, 2003, 2007.)

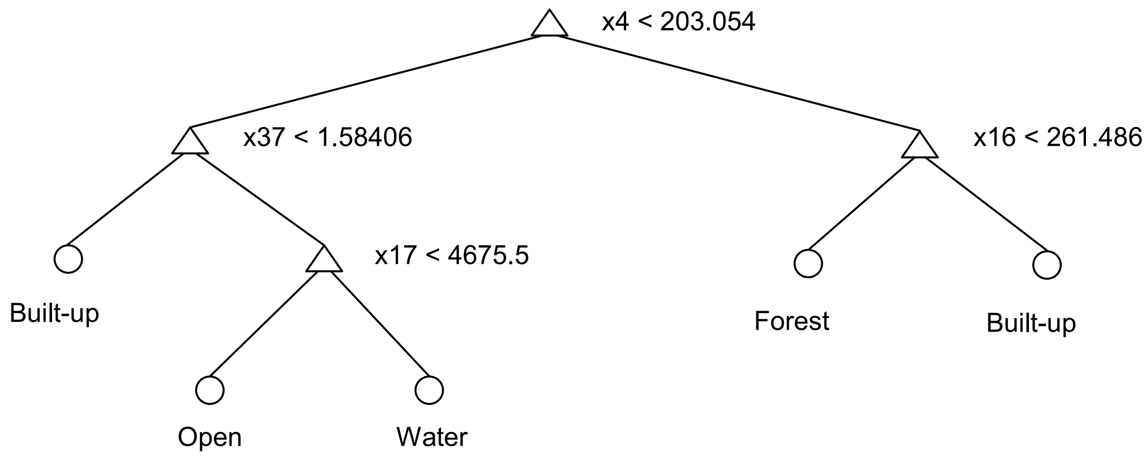

Figure 2. An example of a classification tree (from **IV**).

When the classification tree method is used for a given classification task, there are two main stages in the process: the construction of a tree and the application of the tree to classification. The most useful attributes and splits for the tree are selected automatically by using training data and a splitting criterion. In our studies, the splitting criterion we used was the Gini diversity index, which is a measure of node impurity (for equation, see Breiman et al., 1984, or **IV–VI**). At each node of the tree, a search is made for the split that most reduces the node’s impurity. The original classification tree is normally large and can overfit the training data. Pruning is, thus, needed to obtain a set of smaller subtrees. The best level of pruning can be estimated by using training data and cross-validation. (Breiman et al., 1984; The MathWorks, 2003, 2007.)

The classification tree method can be applied to pixel-based spectral classification of image data in much the same way as more traditional classification algorithms are applied. It can also be used to generate rules for knowledge-based and possibly object-based classification with different types of attributes. Huang and Jensen (1997) demonstrated a knowledge-based approach to wetland classification using SPOT (Satellite Pour l’Observation de la Terre) multispectral imagery and GIS data. They used the C4.5 machine learning algorithm (Quinlan, 1993) to create a decision tree and stored it as production rules in an expert system. Li et al. (2000) used the See5 algorithm (RuleQuest Research, 2012) to create rules for land use classification. A SPOT image and GIS data were used as the input data. Lawrence and Wright (2001) studied land cover/land use classification using Landsat Thematic Mapper (TM) images and a DEM. They used the classification and regression tree analysis (Breiman et al., 1984) available in the S-Plus statistical software package.

Early studies applying classification trees to segments created with the eCognition software were carried out by Hodgson et al. (2003) and Thomas et al. (2003). Hodgson et al. (2003) studied the mapping of urban parcel imperviousness using colour aerial photography and laser scanner derived height data. They used the See5 algorithm to create rules for the land cover classification needed in the process. Segment-based and rule-based classification was one of tested approaches, and it yielded the most accurate final results. Thomas et al. (2003) studied land cover/land use mapping in an urban environment using high-resolution digital aerial imagery. Different classification approaches were also tested in that study. Classification tree rules were created using the S-Plus package. The segment-based classification using the classification tree method yielded a higher level of accuracy than a combined supervised/unsupervised spectral classification, but its accuracy was lower than that enabled by a raster-based spatial modelling method. The spatial modelling method used ancillary data layers and required considerable analyst input. Compared with this, the segment-based approach enabled a significant time saving. Tullis and Jensen (2003) studied the detection of residential houses from IKONOS satellite imagery. The See5 algorithm was used to create classification rules. In addition to other types of information, some contextual information derived using the segmentation method of eCognition was used in the study.

2.4 Mapping built-up areas using coherence and intensity from interferometric SAR images

SAR is an active imaging sensor operating in the microwave region of the electromagnetic spectrum. It transmits signals of electromagnetic energy, illuminates the terrain, and measures the response. (Henderson and Lewis, 1998.) The contents of SAR images differ significantly from optical images, and they are more difficult to interpret. However, SAR images are interesting because they can also be obtained in cloudy and dark conditions. Moreover, they provide information complementary to that obtained from optical data; for example, on surface roughness and soil moisture (Hellwich et al., 2001). In particular, multidimensional SAR images with different polarization channels, frequency bands, and imaging geometries show promise for application in various mapping tasks (Karjalainen, 2010).

SAR interferometry is based on complex images acquired at different locations or at different times (Madsen and Zebker, 1998). Complex images include amplitude and phase information of the backscattered signals and they allow the calculation of coherence. Previous studies have shown that interferometric SAR data, including coherence information as well as conventional backscatter intensity, have considerable potential in land use mapping (Askne and Hagberg, 1993; Wegmüller and Werner, 1995, 1997; Dammert et al., 1999; Strozzi et al., 2000; Weydahl, 2001; Engdahl and Hyyppä, 2003). Coherence is the correlation between the complex images of an interferometric image pair and it provides information on the stability of the target (see, for example, Wegmüller and Werner, 1995). For example, forests have typically lower coherence values than open or urban areas, and interferometric SAR data are, thus, well suited for distinguishing forested land from other land cover classes (Wegmüller and Werner, 1995, 1997; Smith and Askne, 2001). In urban areas, the coherence is usually high due to the stability of the scatterers and it remains high even over long time periods (Strozzi and Wegmüller, 1998; Usai and Klees, 1999; Grey and Luckman, 2003). Coherence information is, thus, also valuable in urban mapping. In backscatter intensity data, built-up areas are characterized by strong reflections from man-made objects such as buildings. The backscattering response can also provide information on the size and density of buildings in an area. (Dong et al., 1997.) The heterogeneous appearance of the areas in the imagery, however, can make automatic interpretation difficult. For example, a suburban area typically comprises houses, roads, other structures, yards, and different types of vegetation. As discussed by Xia and Henderson (1997), the factors affecting the intensity of radar returns from surface objects, especially for urban environments, are many, varied, and complex.

Several studies related to mapping of built-up areas from interferometric SAR data had been conducted prior to Paper **I**. Strozzi and Wegmüller (1998), Del Frate et al. (1999) and Santoro et al. (1999, 2000) tested different approaches based on coherence, intensity, and texture information in the detecting of urban areas. Del Frate et al. (1999) and Santoro et al. (1999) also discussed the possibility of classifying urban areas into subclasses, such as areas with different building densities. Del Frate et al. (1999) included four classes in their classification of the urban area of Rome, Italy: parks, high-density residential areas, low-density residential areas, and water surfaces. The meanings of high-density and low-density areas were not defined in detail, and numerical quality analyses of the results were not presented. Santoro et al. (1999) analyzed coherence, backscatter, and texture values in different types of built-up areas. Grey and Luckman (2003) used coherence information to map urban extent, and Grey et al. (2003) applied coherence information in mapping urban change. Grey and Luckman (2003) found that classification kappa coefficients greater than 90% can be achieved in urban/non-urban classification when image pairs with long time intervals between the images are used. Fanelli et al. (2000) analyzed the causes of decorrelation in urban areas, and Fanelli et al. (2001) and Luckman and Grey (2003) studied the use of coherence images to acquire information on building heights.

The mapping of urban areas has also been addressed in land use and land cover mapping studies with a larger number of classes (Wegmüller and Werner, 1997; Dammert et al., 1999; Strozzi et al., 2000; Bruzzone et al., 2004). For example, Strozzi et al. (2000) used different algorithms and test areas in Europe and their results suggested that land use classification accuracies of approximately 75% are possible with, in the best case, simultaneous forest and non-forest accuracies of approximately 80–85%. Classification accuracy of urban areas, however, was only approximately 30%. Problems in discriminating urban areas were also encountered by Dammert et al. (1999). Better results for urban areas were reported by Bruzzone et al. (2004). These earlier studies used various numbers of European Remote Sensing Satellite (ERS) SAR images and features extracted from them. Engdahl and Hyyppä (2003) created a multitemporal interferometric dataset based on 14 ERS-1/2 Tandem image pairs (Figure 3) and achieved an overall accuracy of 90% when classifying the dataset into six land cover classes. Two urban classes were included: mixed urban and dense urban. The mixed urban class included low-rise and high-rise residential areas and industrial areas. The classification algorithms applied in the previous studies to ERS data were pixel-based methods. Corr et al. (2003) used airborne interferometric polarimetric data and an object-based classification approach based on the eCognition software. Due to the high spatial resolution of the data, it was possible to consider classes such as buildings and trees.

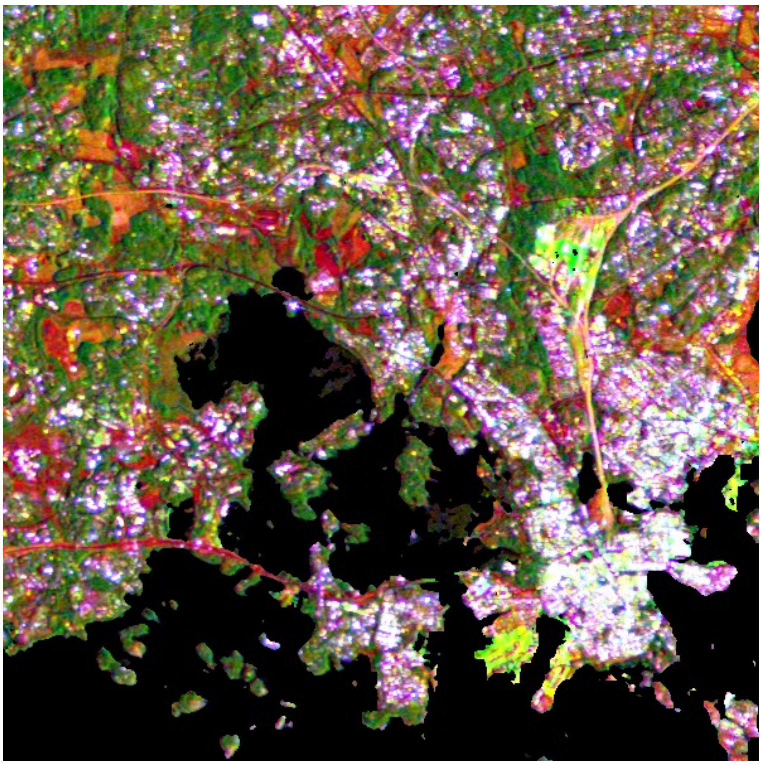

Figure 3. An example of a multitemporal interferometric SAR dataset (from **I**; SAR data © M. Engdahl and ESA AO3-277). The channels of the colour image: temporal average of Tandem coherence images in red, temporal average of backscatter intensity images in green, and average of two long-time coherence images in blue. The figure shows a 12 km × 12 km subarea of the dataset.

2.5 Mapping buildings and land cover using laser scanner and aerial image data

2.5.1 Building detection

Automated building extraction from aerial imagery for mapping and map updating purposes has been addressed in a considerable number of studies during the past decades (see, for example, Jamet, 1998; Mayer, 1999; Baltsavias et al., 2001; Niederöst, 2003; Baltsavias, 2004). This review concentrates on building detection research and on studies that have used laser scanner data. It should be noted that height data obtained from aerial images by using image matching techniques can be used in much the same way as height data from laser scanning as will be shortly described.

Similar to SAR, laser scanners are active instruments, but they usually make use of the visible or near-infrared (NIR) regions of the spectrum (Campbell, 2002). The laser systems used in airborne laser scanning are typically pulsed time-of-flight measurement systems (also called lidars), which measure the travel time of light from the system to a reflective target surface and back (Beraldin et al., 2010). Laser scanning provides a point cloud with xyz coordinates and typically also the intensity of the reflected pulses. Depending on the type and orientation of the surface, the systems can also produce two or more return pulses (echoes), typically up to four (Beraldin et al., 2010). The first pulse is typically obtained from tree canopy or the roof of a building and the last pulse from the ground if the pulse has penetrated the tree canopy or hit the edge of the building roof. In the middle of smooth surfaces, such as building roofs and bare ground, only one return is obtained, or the first pulse and last pulse heights are nearly the same, depending on the system. There can also be intermediate pulses. Full-waveform laser scanning, which was not used in our study, provides the full shapes of the return echoes (Beraldin et al., 2010).

Airborne laser scanners became available in the early 1990s (Beraldin et al., 2010) and were soon applied to automated building detection and mapping (e.g., Hug, 1997; Lemmens et al., 1997). The detailed height data available from laser scanning is particularly useful in distinguishing high objects such as buildings and trees from the ground surface and lower objects. Prior to the aforementioned studies, the use of high-resolution elevation data for building extraction had already been studied by using elevation data derived from images (e.g., Weidner and Förstner, 1995). Weidner and Förstner (1995) used mathematical morphology (Haralick et al., 1987) to first derive an approximation of the ground surface. The difference between the elevation data and the ground surface was then used as a basis for building detection. Thresholding was carried out, connected components (segments) were formed, and valid building segments were selected by using a minimum size criterion. The segments were refined using locally adapted thresholds and finally used as a basis for building reconstruction. Hug (1997), who used laser scanner data, also applied a morphology-based filter to detect "surface objects". The surface objects were then classified into buildings and vegetation using reflectance data from laser scanning, elevation texture, and surface orientation. The method and the usefulness of different classification criteria were tested within an area measuring 1.5 km × 1.5 km and containing more than 400 buildings. The results were reported as error rates, the lowest of them being 21%.

Since the late 1990s, a large number of methods for building detection using laser scanner data has been presented (see references in **III** and **V**). The building detection methods applied often use DSMs in raster format, but they can also be based on the classification of the original laser points (Axelsson, 1999; Vosselman et al., 2004) or use point data in addition to raster data (Hug, 1997; Tarsha-Kurdi et al., 2006). Many studies have been conducted using laser scanner data alone (e.g., Morgan and Tempfli, 2000; Forlani et al., 2006; Zhang et al., 2006; Meng et al., 2009), but many others have relied on both laser scanner and aerial image data (e.g., Haala and Brenner, 1999; Rottensteiner et al., 2005; Lee et al., 2008). Some studies have combined laser scanner data and satellite imagery (Muller et al., 2004; Sohn and Dowman, 2007). Most of the methods presented in literature are based on step-wise classification approaches to distinguishing buildings from other objects. Most of them also have applied object-based analysis, at least in some of the processing steps. Some methods begin by segmenting the data into spatially continuous, homogeneous regions or surfaces that are then classified (e.g., Hofmann et al., 2002; Vosselman et al., 2004; Forlani et al., 2006). Others first apply classification to individual pixels and then proceed to form meaningful objects on the basis of the classification results.

Similarly to the early studies described above (Weidner and Förstner, 1995; Hug, 1997), the first step in the building detection methods is typically to separate the elevated objects, i.e., mainly buildings and trees, from the ground surface. The ground surface can be determined by using a filtering algorithm. Due to the importance of digital terrain models (DTMs), filtering of laser scanner data has been a topic of active research. Typical approaches include morphological filtering, progressive densification, surface-based filtering, and segment-based filtering (Briese, 2010). In building detection studies, a normalized DSM (nDSM) is often produced after filtering by subtracting the DTM from the DSM (e.g., Brunn and Weidner, 1998; Voegtle and Steinle, 2003; Rottensteiner et al., 2005).

In addition to separating high objects from the ground surface, another important task in building detection is to distinguish buildings from trees and other vegetation. Different types of information have been used to separate buildings and vegetation, including the following:

- Height texture (e.g., Hug, 1997; Maas, 1999; Oude Elberink and Maas, 2000) or surface roughness (e.g., Brunn and Weidner, 1998; Alharthy and Bethel, 2002; Rottensteiner et al., 2005),
- Reflectance data from images, typically the normalized difference vegetation index (NDVI) (e.g., Vögtle and Steinle, 2000; Rottensteiner et al., 2005; Zhan et al., 2005),
- Reflectance data (intensity) from laser scanning (e.g., Hug, 1997; Tóvári and Vögtle, 2004; Luzum et al., 2005),
- Difference between first pulse and last pulse laser scanner data (e.g., Oude Elberink and Maas, 2000; Alharthy and Bethel, 2002; Voegtle and Steinle, 2003),
- Size and/or shape of objects (e.g., Morgan and Tempfli, 2000; Voegtle and Steinle, 2003; Tóvári and Vögtle, 2004).

In addition to various step-wise and rule-based approaches specifically developed for the building detection task, several general-purpose classification methods have been used, including unsupervised clustering (Haala and Brenner, 1999; Miliaresis and Kokkas, 2007), supervised maximum likelihood classification (Maas, 1999; Tóvári and Vögtle, 2004; Luzum et al., 2005), fuzzy membership functions (Voegtle and Steinle, 2003; Tóvári and Vögtle, 2004; Zhan et al., 2005), and the Dempster–Shafer method (Rottensteiner et al., 2005). Classification or decision trees have also been used to distinguish buildings and other classes in several studies during the last few years (Zingaretti et al., 2007; Im et al., 2008; Mancini et al., 2009). Zingaretti et al. (2007) and Mancini et al. (2009) used the classification tree method in combination with a boosting algorithm, which combines several trees. In 2006, when Paper **IV** was published, the classification tree method had not yet been widely applied to the analysis of laser scanner data. As has been mentioned in Section 2.3, Hodgson et al. (2003) used the method for the mapping urban parcel imperviousness using colour aerial photography and laser scanner derived height data. Another example is the study by Ducic et al. (2006), who applied the method for vegetation classification from full-waveform laser scanner data. Jung (2004) had applied decision trees in the detection of buildings from grey-scale aerial images. The results for several trees were also combined in that study. Jung (2004) used the classification results as a basis for change detection of buildings. Knudsen and Nielsen (2004) had also tested the classification tree method to find useful features for building detection from aerial image data. Their study was also related to research on change detection.

Most of the early building detection studies using laser scanner data concentrated on method development. Some numerical quality analyses were also presented (e.g., Hug, 1997; Maas, 1999; Voegtle and Steinle, 2003; Vu et al., 2003), but, in general, testing of the methods received less attention. In later studies, quality evaluation of the results has become more important, and some papers have specifically concentrated on this topic (Zhan et al., 2005; Pfeifer et al., 2007; Rottensteiner et al., 2007; Rutzinger et al., 2009). Numerical accuracy estimates depend on study areas, datasets, and methods used in accuracy estimation. In the case of large buildings, accuracies above 95% have been achieved. Small buildings are more problematic. For example, Rottensteiner et al. (2007) found that 95% of all buildings larger than 70 m^2 could be detected, but buildings smaller than 30 m^2 could not be detected. The point density of laser scanner data in the study was about 1 point/m^2. To obtain a good understanding of the quality of building detection results, the use of different quality measures, including both object-based and pixel-based measures, is considered important (e.g., Song and Haithcoat, 2005; Zhan et al., 2005; Rutzinger et al., 2009). As the size of buildings is an important factor affecting the quality of the results, it is also important to analyze the results separately for different building sizes (Zhan et al., 2005; Rottensteiner et al., 2007; Rutzinger et al., 2009). In later building detection studies, interest has also been focused on the comparison of different methods and input features (Luzum et al., 2005; Pfeifer et al., 2007; Rottensteiner et al., 2007; Khoshelham et al., 2010).

Regarding the use of first pulse or last pulse laser scanner data, Steinle and Vögtle (2000) discussed the effects of different laser scanning modes on the results of building recognition and reconstruction. They demonstrated how building models acquired from first pulse data are systematically larger and those acquired from last pulse data are systematically smaller than reference models. This is due to the fact that, at the edges of the buildings, the first pulse returns are obtained from the roof and the last pulse returns from the ground surface. Similar results were obtained by Ahokas et al. (2004). According to Voegtle and Steinle (2003), better positional accuracy for building models can be obtained by determining the mean outline of the buildings from the first pulse and last pulse data. When analyzing the first pulse and last pulse data separately, Steinle and Vögtle (2000) found that the first pulse data agreed better with cadastral maps or manually measured models. The advantage in using last pulse data, on the other hand, was that there was then less vegetation and fewer objects on the roofs to confuse the data. Other studies have also indicated that there is some evidence that the use of last pulse data is advantageous in building detection, at least in some of the processing steps (e.g., Voegtle and Steinle, 2003; Zhang et al., 2006; Rottensteiner et al., 2007). Some studies, on the other hand, have specifically used first pulse data (e.g., Tarsha-Kurdi et al., 2006). To the best of the author's knowledge, no comparative study with a detailed numerical quality analysis concerning the results of automated building detection using first pulse or last pulse data had been carried out before Paper **III**. An example of DSMs derived from first pulse and last pulse laser scanner data can be seen in Figure 4.

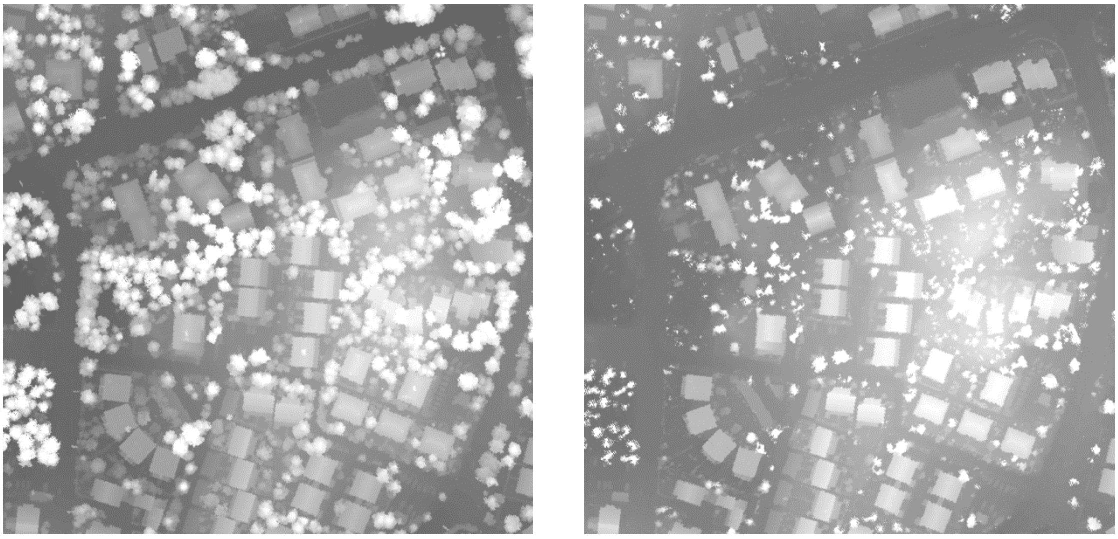

Figure 4. DSMs derived from first pulse (left) and last pulse (right) laser scanner data in a low-rise residential area (part of the study area and data used in **III**).

2.5.2 Land cover classification

Methods specialising in building detection also have to deal with land cover classes other than buildings. In practice, at least trees and the ground surface have to be considered. Some researchers have also segregated different ground classes, i.e., grass from streets or bare soil (Haala and Brenner, 1999; Rottensteiner et al., 2005).

Laser scanner and aerial image data have also been used in more general land cover classification studies. As is already discussed in Section 2.3, Thomas et al. (2003) and Hodgson et al. (2003) carried out land cover/land use classifications in which image segmentation and classification trees were applied. Other land cover classification studies based on aerial image data have been carried out, for example, by Walter (2004), Kressler et al. (2005), Sanchez Hernandez et al. (2007), and Xu et al. (2010). The first three of these studies were related to change detection with regard to existing map databases. Laser scanner data alone have been used, for example, by Brennan and Webster (2006), Im et al. (2008), Chehata et al. (2009), and Garcia-Gutierrez et al. (2009). Chehata et al. (2009) used full-waveform laser scanner data. The other three studies used intensity information in addition to height, which is important in distinguishing classes such as grass and roads. Combinations of laser scanner and aerial image data were used by, for example, Gamba and Houshmand (2002), Huang et al. (2008), and Zhou and Troy (2008).

Most of the above studies used object-based methods. Some of them also used classification trees (Im et al., 2008; Garcia-Gutierrez et al., 2009) or the random forests method (Chehata et al., 2009), which is one of the more advanced methods combining several trees. Promising results have been reported by the researchers. For example, Im et al. (2008) achieved overall classification accuracies in excess of 90% by using height and intensity data from laser scanning. Segmentation and the decision tree method were applied in classification involving five land cover classes. Huang et al. (2008) used aerial imagery and height and intensity data from laser scanning to classify land into four classes by means of a knowledge-based method. The overall accuracies achieved were about 94%. Sanchez Hernandez et al. (2007) used multispectral aerial imagery and achieved an overall accuracy of 75% when applying an object-based approach with user-defined classification rules. Six land cover classes were included in the results.

As described above, laser scanner data are typically combined with aerial image data in classification studies. They have also been combined with high-resolution optical satellite images (e.g., Hofmann, 2001; Chen et al., 2009). Land cover classification studies comparing or utilizing many different types of aerial and satellite data, however, are rare. One example is the study by Gamba and Houshmand (2002), who extracted land cover, DTMs, and 3D building models by using aerial SAR, laser scanner, and aerial image data. In land cover classification, only aerial image and laser scanner data were used.

2.6 Change detection of buildings using laser scanner and aerial image data

As presented in the previous section, laser scanner and aerial image data are well suited for automated detection of buildings. They are, thus, also promising sources of data for developing automated change detection methods for building databases. Different basic approaches for developing such methods are possible (for general principles of change detection techniques used in remote sensing, see, for example, Li et al., 2002, and Lu et al., 2003). If both old and new laser scanner and/or aerial image datasets are available, change detection can be based on the comparison of these. Another basic approach with regard to change detection is to detect buildings from new data and compare the results with an existing building map to detect changes. This approach is needed if laser scanner and image data corresponding to the state of the old map are not available. It is also feasible from the point of view of a mapping agency that maintains a topographic database and aims to detect changes between the database and up-to-date image data (Holland et al., 2008).

Prior to **II**, the potential of laser scanner data in change detection of buildings had been demonstrated by Murakami et al. (1999). Their method used multitemporal data and was simply based on subtracting one laser scanner derived DSM from another. Steinle et al. (1999) had presented change visualisations between a 3D computer-aided design (CAD) model and laser scanner DSMs based on overlays and pointwise comparisons. The detection of damage after events such as earthquakes was mentioned as a possible application area. Hofmann et al. (2002) discussed the transformation of 2D building data into 3D building data with higher accuracy. Segmentation was applied to laser scanner data, and building segments were detected by using a map and the laser scanner data. Hofmann et al. (2002) mention also that a number of buildings not presented on the map could be detected. Change detection between the datasets, however, was not directly discussed in the paper. Change detection studies based on aerial imagery had been carried out, for example, by Hoffmann et al. (2000) and Knudsen and Olsen (2002). Hoffmann et al. (2000) used DSM data and multispectral data, both obtained from digital airborne imagery. They studied segment-based detection of buildings using the eCognition software. Change detection between map data and the building detection results was demonstrated briefly, without describing the method in detail. Knudsen and Olsen (2002) presented a method that was based on pixel-based spectral classification of aerial image data followed by change detection. Change detection included comparison between buildings in a topographic database and the classification results and some postprocessing steps. An image showing change pixels was obtained as the final product. The method was tested in a suburban area in Denmark. A specific problem proved to be flat asphalt-covered roofs, which were difficult to separate from road surfaces.

More change detection studies were published between **II** and **V**. Knudsen and Olsen (2003) continued their study and presented more test results. Further developments of the method included the use of DSM data (Olsen, 2004; Olsen and Knudsen, 2005). Vosselman et al. (2004, 2005) used laser scanner data, colour imagery (in the first study), and a segment-based classification approach to detecting buildings. The change detection was carried out between building objects in a topographic database and the detected buildings. To take into account differences between the building objects in these datasets, the method employed morphological operations, shifting of objects, and mapping rules determining which objects are mapped in the database. The method developed by Rottensteiner (2007, 2008) used a DSM and multispectral imagery and included pixel-based and region-based classification steps to detect buildings. An existing building map was used as additional input data in a Dempster–Shafer fusion process applied in building detection to provide an indication of where buildings are likely to exist. Change detection was carried out between the building map and the building detection results. A topological clarification stage including splitting and merging of building objects was included to achieve topological consistency between the datasets. Overlaps between objects and morphological analysis were used in change detection. Buildings and building parts were classified as confirmed, changed, new, or demolished. Holland et al. (2008) used digital aerial image data and a DSM created from the images and tested different classification approaches. One of these was the classification tree method. A change detection approach for detecting demolished and new buildings was also developed. The change detection was carried out between building objects in a topographic database and the classification results. Overlap percentages were used to detect demolished buildings. New buildings were found from the classification results after masking out roads, rail tracks, water bodies, and buildings in the database, and after filtering out small objects. In all these methods, change detection was carried out between existing map data and building detection results. Map data were also used to determine training areas (Knudsen and Olsen, 2002, 2003), to give additional support for deciding whether a pixel belongs to a building or not (Rottensteiner, 2007, 2008), and to mask out areas where buildings are not likely to occur (Holland et al., 2008).

Change detection approaches concentrating on the verification of map data have also been developed. Similar to the methods discussed above, these methods use existing map data and new remotely sensed data, but they use the map data more directly as a starting point, for example, by analyzing building boundaries (Ceresola et al., 2005; Champion, 2007). New buildings are then extracted separately. Bouziani et al. (2010) presented a knowledge-based change detection method for the detection of demolished and new buildings from satellite images of very high resolution. Different object properties, including possible transitions and contextual relationships between object classes, were taken into account. Map data were used to determine processing parameters and to learn the object properties. More methods based on multitemporal laser scanner or image data have also been developed (Jung, 2004; Vögtle and Steinle, 2004; Vu et al., 2004; Butkiewicz et al., 2008; Nakagawa and Shibasaki, 2008). For example, Vögtle and Steinle's (2004) method used multitemporal laser scanner data and compared DSMs in an object-based manner by analyzing building objects that were first extracted from the DSMs.

Numerical quality evaluations for change detection methods using new DSM data and aerial image data to detect buildings and comparing the results with existing map data to detect changes have been presented by Olsen (2004), Olsen and Knudsen (2005), Holland et al. (2008), and Rottensteiner (2008). The most extensive of these was the study by Holland et al. (2008), who carried out a production test on two test sites, covering 23 km^2 and 25 km^2. In the case of the first area, 142 potential changes were detected, and 25% of these were real changes. One real change was missed. With the second area, the number of detected changes was 427, and 18% of these were real changes. The number of missed changes was 14. According to Holland et al. (2008), the time needed to identify changes was reduced by 50% when compared with a manual process, and the automated change detection process was considered very useful by an operator. Olsen (2004) and Olsen and Knudsen (2005) used a relatively small study area with about 70 buildings. According to Olsen (2004), about 50% of the changes were found and there were problems in detecting new buildings because their spectral response was different from existing buildings in the area. There were also many false alarms. Better results with almost all changes detected were reported by Olsen and Knudsen (2005). Colour aerial images were used in the first study and colour-infrared images in the latter one. Rottensteiner (2008) used simulated rather than real changes in quality evaluation.

A comparison of different change detection (or building detection) methods was carried out in a EuroSDR (European Spatial Data Research) project (Champion, 2009; Champion et al., 2009). The tested methods included those presented by Olsen and Knudsen (2005), Champion (2007), Matikainen et al. (2007), and Rottensteiner (2008). Because of differences in the outputs of the change detection methods (e.g., definitions of classes), the comparisons were based on updated building maps (or building detection results) for most of the methods. Our method (Matikainen et al., 2007) corresponded to the building detection method based on classification trees presented in **IV** and **V**. The methods were tested in three study areas using different datasets (all of the methods were not tested in all of the areas; our method was tested in two areas). Up-to-date building databases were used as reference data. Old databases were created by simulating changes. None of the methods was clearly better than the others. The results varied depending on area and accuracy estimate, and each method achieved the highest accuracy in some cases. Generally, all methods found real (simulated) changes relatively well (building-based completeness 79–99%), but there were many false detections (building-based correctness 45–76%). Detailed analyses and discussions of the results and of the different factors affecting the results are presented in Champion (2009) and Champion et al. (2009).

3. MATERIALS AND METHODS

3.1 Study areas and materials

A summary of the study areas used in **I–VI** is presented in Table 1. Table 2 summarizes the datasets used in the study. Further details of the datasets and their preprocessing can be found in **I–VI** and in the original references mentioned in the table.

Table 1. Summary of the study areas.

Paper	Location of study area	Description of study area
I	Helsinki metropolitan region and its surroundings; total area 1800 km^2	• Various built-up areas, forests, and agricultural land • Entire area classified; subareas used for further analysis and quality evaluation
II	Otaniemi in Espoo, near Helsinki; total area 2.0 km^2	• Campus area with large buildings, residential area with high-rise and low-rise buildings • Most of the area relatively flat, low hills • Coniferous and deciduous vegetation • Leaves on trees at the time of acquiring the laser scanner data

III–VI	Espoonlahti in Espoo; total area 2.5–5.3 km^2 (outlines different in each paper)	• Suburban area with industrial, high-rise residential and low-rise residential areas
		• In **V**: a new residential area with plenty of changes was included
		• Varying topography with low hills
		• Plenty of coniferous and deciduous vegetation
		  • No leaves or small leaves on trees: laser scanner data used in **III** and **IV**, E-SAR data used in **IV** and **VI**, QuickBird data used in **VI**
		  • Trees in full leaf: laser scanner data used in **V** and **VI**, aerial image data used in **III** and **IV**, aerial image data used in **V** and **VI**

Table 2. Summary of the datasets.

Paper	Data used in study	Pixel width	Original data source	Purpose of use
I	A multitemporal interferometric SAR dataset (1995–1996) with 8 channels including intensity, coherence, and texture information. A water mask created using the dataset. (Engdahl and Hyyppä, 2003)	20 m	14 ERS-1/2 Tandem image pairs (Engdahl and Hyyppä, 2003)	Input data for land use classification and further analysis of built-up areas. Water areas were excluded by using the water mask.
I	1313 reference points representing various land cover classes (Engdahl and Hyyppä, 2003)		Aerial photographs, topographic maps, forest inventory information (Engdahl and Hyyppä, 2003)	Reference data for quality evaluation
I	Reference maps on land use	20 m	1:50 000 Map Database (NLS) and a forest map (FM-Kartta Oy)	Reference data for method development and quality evaluation
I	Building maps	2 m	Topographic Database (NLS), a building map, and a DEM (FM-Kartta Oy)	Reference data for method development and quality evaluation
II	DSM (maximum height), DTM and intensity image from laser scanning (5 September 2002)	0.6 m	TopEye laser scanner data (2–3 points/m^2)	Input data for building detection
II	Old building map (2000)	0.6 m	Topographic Database (NLS)	Reference data for method development and input data for change detection
II	New building and forest map (2001)	0.6 m	Building and forest maps (FM-Kartta Oy)	Reference data for method development and quality evaluation

Table 2. (cont.)

Paper	Data used in study	Pixel width	Original data source	Purpose of use
III, IV	First pulse DSM (maximum height) (**III**), last pulse DSM (minimum height), ground and height classification of laser points (14 May 2003)	0.3 m	TopoSys FALCON II laser scanner data (10 points/m^2)	Input data for building detection
III, IV	Aerial colour ortho image mosaic (red, green, and blue channels) (26 June 2003)	0.3 m	Scanned aerial imagery (FM-Kartta Oy)	Input data for building detection
III, IV	Building map (2003)	0.3 m	A city base map (City of Espoo)	Reference data for method development (**III**), classifier training (**IV**), and quality evaluation (**IV**)
III	Building map (an improved version) (2003)	0.3 m	A city base map (City of Espoo)	Reference data for quality evaluation
III, IV	Forest map (2001)	0.3 m	A forest map (FM-Kartta Oy)	Reference data for method development (**III**) and classifier training (**IV**)
IV, VI	E-SAR L band and X band images (used channels: LHH, LHV, LVV, XHH, XVV) (transformed into a new coordinate system for **VI**) (2 May 2001) (Matikainen et al., 2004)	1 m (**IV**, **VI**); 0.3 m (**VI**)	E-SAR data (DLR, German Aerospace Center)	Input data for land cover classification
IV	87 reference points (Matikainen et al., 2004)		E-SAR imagery, aerial ortho imagery and map data (several sources)	Reference data for classifier training
IV	519 reference points (Matikainen et al., 2004)		Aerial ortho imagery and map data (City of Espoo)	Reference data for quality evaluation

Table 2. (cont.)

Paper	Data used in study	Pixel width	Original data source	Purpose of use
V, VI	DSMs (maximum and minimum height), ground and height classification of laser points (12 July 2005)	0.3 m	Optech ALTM laser scanner data (2–4 points/m^2)	Input data for building detection (**V**), change detection (**V**), and land cover classification (**VI**)
V, VI	Aerial ortho image mosaic (red, green, blue, and NIR channels) (1 September 2005)	0.3 m	Intergraph DMC digital aerial images	Input data for building detection (**V**) and land cover classification (**VI**)
V	Old building map (2000)	0.3 m	Topographic Database (NLS)	Input data for change detection
V	New building map (2005)	0.3 m	Different versions of a city base map (City of Espoo)	Reference data for method development, classifier training and quality evaluation
VI	QuickBird satellite image (red, green, blue, and NIR channels) (27 May 2003)	2 m	QuickBird satellite image (original pixel width 2.4 m)	Input data for land cover classification
VI	297 reference points (updated version of the points used in **IV**)		Aerial ortho imagery (**V,VI**), DSM from laser scanning (**V,VI**), a city base map and a city plan (City of Espoo)	Reference data for classifier training
VI	269 reference points (updated version of the points used in **IV**)		Aerial ortho imagery (**V,VI**), DSM from laser scanning (**V,VI**), a city base map and a city plan (City of Espoo)	Reference data for quality evaluation

DMC = Digital Mapping Camera, ALTM = Airborne Laser Terrain Mapper

3.2 Methods

3.2.1 Method development for mapping built-up areas

Object-based interpretation methods for mapping built-up areas were developed in the study. Specifically, they were developed for:

- Mapping built-up areas using a multitemporal interferometric SAR dataset (**I**),
- Building detection using laser scanner and aerial image data (**II**–**V**),
- Change detection of buildings using building detection results and an old building map (**II** and **V**), and
- Land cover mapping using classification trees, test field points, and various input datasets (**IV** and **VI**).

The developed methods are described in Section 4 together with the experimental results obtained when using the methods. The methods and results are discussed in Section 5, specifically taking into account the hypothesis and objectives of the study. Further details of the methods can be found in **I–VI**.

The most important software packages used in the study included eCognition (Trimble Geospatial, 2012a), MATLAB (The MathWorks, 2012), and TerraScan (Terrasolid, 2012). Table 3 summarizes the main tools and algorithms used. These tools and algorithms may be considered as the building blocks for the interpretation methods developed and tested in the study. The processing steps were planned specifically for each application, but the developed methods also had some common characteristics. The multiresolution segmentation method of eCognition was used in segmentation in each paper. Due to the widely different datasets and objects of interest, the parameters were selected separately for each dataset and application. Examples of different segmentations can be seen in Figure 5. Details of these segmentations may be found in **I** and **VI**. The classification tree tools of the MATLAB Statistics Toolbox were applied to building detection and land cover classification in **IV–VI**. TerraScan software was used to classify pointwise laser scanner data. The programming tools of the MATLAB software were used to implement methods and tools that were not directly available in the software packages. For example, change detection methods for buildings and classification procedures that applied the classification tree tools were implemented with MATLAB.

Table 3. The main software tools used in method development and testing (different versions of the software were used in different papers; some versions of eCognition were called Definiens).

Software	**Method/algorithm**	**Purpose of use**	**Paper**
eCognition (Definiens) (Trimble Geospatial, 2012a)	Multiresolution segmentation (Baatz and Schäpe, 2000)	Segmentation	**I–VI**
	Nearest neighbour (NN) classification (e.g., Jensen, 2005)	Classification	**I**
	Fuzzy membership functions (e.g., Tso and Mather, 2001; Benz et al., 2004)	Classification	**I–III**
	Calculation of various segment attributes (Definiens, 2010)	Properties of segments for classification	**I–VI**
MATLAB (The MathWorks, 2012)	Classification tree method (Breiman et al., 1984; The MathWorks, 2007)	Definition of classification rules, classification	**IV–VI**
	Other tools, e.g., programming, statistical analysis, image processing (The MathWorks, 2007)	Analyses for method development; quality evaluation; classification (**III–VI**); change detection of buildings (**II**, **V**)	**I–VI**
TerraScan (Terrasolid, 2012)	Ground classification (Axelsson, 1999, 2000); classification on the basis of height from ground	Classification of laser points	**II–VI**

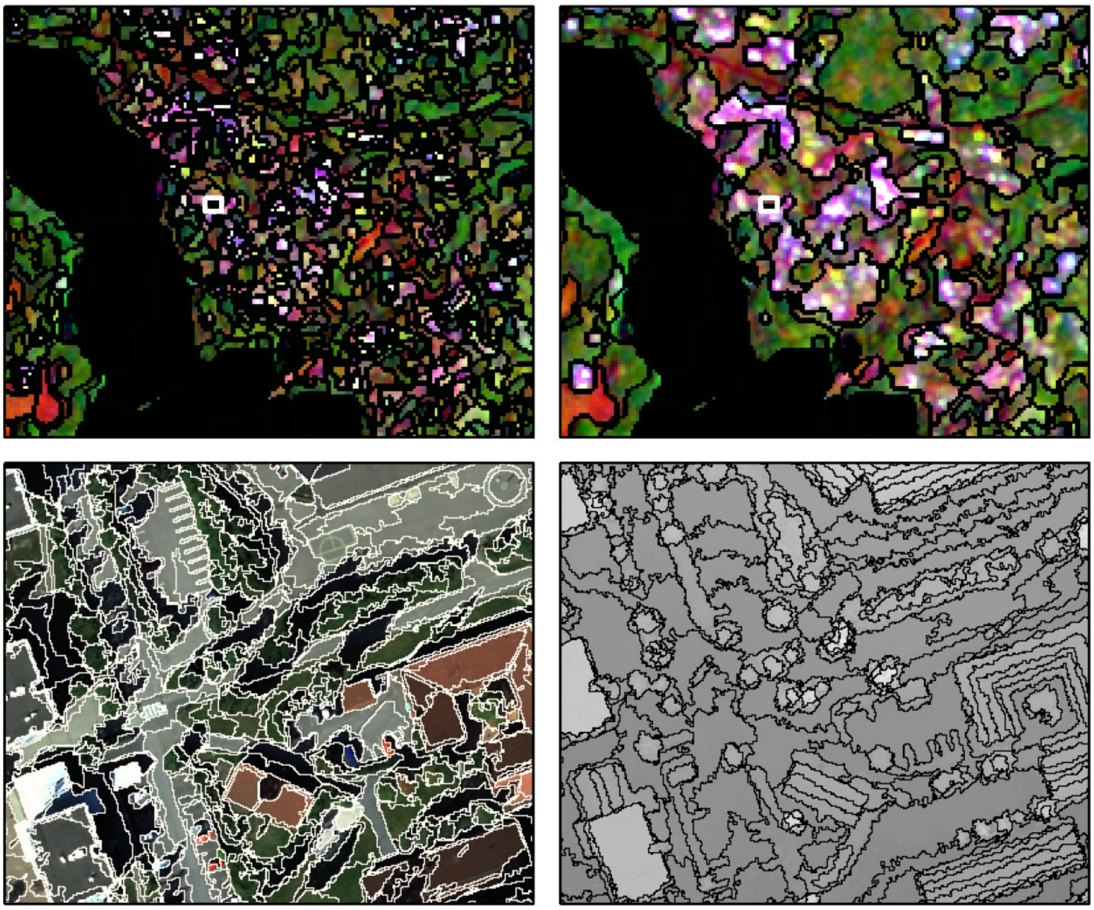

Figure 5. The segmentation of a multitemporal interferometric SAR dataset (top), aerial image data (bottom, left), and a DSM (bottom, right) using the multiresolution segmentation method in eCognition. The segmentations on the top row were used as the bases for land use classification and building density classification in **I**. The segmentations on the bottom row were used as the bases for land cover classifications in **VI**. The small white rectangles in the images on the top row show the location of the area presented in the images on the bottom row. SAR data © M. Engdahl and ESA AO3-277.

3.2.2 Quality evaluation

The quality of the interpretation results was evaluated by comparing them with the reference data. Validation areas separate from training areas were used. Typically, a part of the study area was defined as a training area, and the validation of the results was carried out in other areas. The quality evaluation methods were implemented using MATLAB.

Confusion matrices and accuracy estimates derived from these matrices (Helldén, 1980; Congalton and Green, 1999) were used to evaluate the results. The following accuracy estimates were used:

- Completeness, which shows the percentage of correctly classified validation data. Completeness corresponds to interpretation accuracy or the producer's accuracy, and it is calculated separately for individual classes.
- Correctness, which shows the percentage of classified data belonging to the same class in the validation data. Correctness corresponds to object accuracy or the user's accuracy, and it is calculated separately for individual classes.

- Mean accuracy, which is a combination of the above two measures and is calculated separately for individual classes (for equation, see Helldén, 1980, or **III**).
- Overall accuracy, which shows the total percentage of correctly classified data, including all classes.

Various names have been used for the first two of these measures in remote sensing literature. Generally, “producer’s accuracy” and “user’s accuracy” are widely-used terms, but “completeness” and “correctness” (Heipke et al., 1997) have been commonly used in the literature on building extraction. Accuracy estimates are typically calculated by comparing classification results with the reference data pixel by pixel. Object-based completeness and correctness were also used in our building detection studies. In this case, entire building objects were considered as either correct or incorrect. The criteria for determining this were usually based on the percentage of the building object’s area that had been correctly classified. Similar approaches have also been used by other authors (e.g., Rottensteiner et al., 2007; Rutzinger et al., 2009). In **III**, further development was carried out to acquire more detailed information on the building detection results obtained by using first pulse or last pulse laser scanner data. The classification results inside and outside each reference building, excluding a buffer zone around the boundary, were analyzed, and the buildings were classified into quality categories such as *inside and outside correct* and *inside correct, outside incorrect*.

In the change detection study of buildings (**V**), special arrangements were also needed to evaluate the change detection results. Reference results were first created by carrying out change detection between old and new building maps. The change detection method developed in the study was used for this. A confusion matrix was then formed by comparing the actual change detection results with the reference results, building by building, and completeness and correctness could be calculated. These accuracy estimates, and also the object-based completeness and correctness of the building detection results (**II** and **V**), were calculated separately for buildings of different sizes. Similarly to Zhan et al. (2005), Rottensteiner et al. (2007), Champion et al. (2009) and Rutzinger et al. (2009), curves showing the accuracy estimates as a function of building size were then created (**V**).

4. RESULTS

4.1 Mapping built-up areas using a multitemporal interferometric SAR dataset

4.1.1 Land use classification

Mapping of built-up areas using a multitemporal interferometric SAR dataset included coarse land use mapping and further classification of built-up areas into subclasses. The SAR dataset had been prepared in an earlier study, and the interferometric processing and most of the other preprocessing steps have been described in Engdahl and Hyyppä (2003). For our study, the dataset was available as an 8-channel image including intensity, coherence, and texture information.

In the land use classification stage, homogeneous regions from segmentation were classified into *built-up areas*, *forests* and *open areas* by using the supervised nearest neighbour (NN) classification method. The initial training areas were defined manually and they covered about 0.12% of the total land area in the imagery. Four different channel combinations, including intensity, coherence and texture information, were tested for the purpose of classification. The mean values of the segments were used. An important objective in classification was the detection of built-up areas as large entities. To achieve such a classification, contextual information in the form of texture (e.g., Dekker, 2003; Dell'Acqua and Gamba, 2003) or neighbourhood relationships between segments (e.g., Johnsson, 1994b; Benz et al., 2004) can be useful. For example, a significant part of low-rise residential areas is typically covered by vegetation, which should be taken into account in order to recognize entire residential areas as being *built-up*. The texture channel of the dataset had been calculated using a large window size, and the mean value for a segment thus provided information on intensity variations both within the segment and its neighbourhood. As an alternative to the texture channel, we tested the use of information on the neighbouring segments' classes. Segments first classified as *forests* or *open areas*, but which were mainly surrounded by *built-up area*, were grouped together with *built-up area*.

The accuracy of the land use classification results was estimated by comparing the results with reference points and a reference map. The 1313 reference points were distributed over a large part of the study area and represented homogeneous plots selected manually using, for example, aerial imagery (Engdahl and Hyyppä, 2003). The map provided a more complete coverage of a smaller area, but it contained information that had been generalized for map presentation. Compared with the reference points, the highest overall accuracy achieved in land use classification was 97%. The reference points in dense urban areas, i.e., city centre, were recognized as *built-up* with an accuracy of 100%. In low-rise residential areas, high-rise residential areas, and industrial areas, the best results for the *built-up* class were 94%, 98%, and 99%, respectively. The texture channel appeared to be useful in recognizing built-up areas, especially low-rise areas, as being *built-up*. When the texture channel was not used, the interpretation accuracy of *built-up areas* could be clearly improved by using information on the classes of the neighbouring segments. The drawback in the use of the contextual information was that some open areas and forests were incorrectly classified as being *built-up*.

Compared to the reference map, the accuracy of the results was generally somewhat lower than when compared to the reference points. The overall accuracy of the best classification result was 86%. In high-rise areas and industrial areas, the accuracy for the *built-up* class was nearly the same as the corresponding accuracy obtained using the reference points. In low-rise areas, the best accuracy for the *built-up* class was clearly lower when compared with the reference map (78%). A visual analysis revealed that the low-rise areas that were not detected were often forested areas and not clearly visible in the imagery. On the other hand, small areas within forests, especially rocky or hilly areas, were sometimes misclassified as being *built-up*.

4.1.2 Further analysis of built-up areas

The feasibility of the interferometric SAR dataset for distinguishing different types of built-up areas was also investigated. The characteristics of low-rise areas, high-rise areas, and industrial areas presented on topographic maps were first compared. Segments feasible for presenting different built-up areas on a map were created. Various attributes of the segments were calculated (mean values, standard deviations, textural features), and attribute histograms were constructed. A significant overlap existed between the histograms of the three classes, and it was thus difficult to distinguish them from each other. A probable reason for this was that areas with varying building density and vegetation cover can occur in each of the three classes.

The relationships between the image data and building density were then investigated (see Figure 6). In this case, building maps were used to estimate the building density of the segments. Two building maps matching different points in time were used to ensure good correspondence with the image data: an old map, which was older or approximately from the same period as the imagery, and a new map, which was newer than the imagery. Areas with clear differences between the maps were excluded. Building heights were also available, and the analysis was carried out with and without the height data. Scatter plots and linear regression analyses showed that a clear dependence existed between the building density of an area and its mean intensity and coherence in the image data. The highest correlation coefficient (0.811) and the highest coefficient of determination (0.657) were obtained for segment brightness, which is an attribute describing the mean value of the mean values in several channels of the image data. Segments with a building density of 0 or over a given threshold value were excluded from the analysis, because the aim was to analyze built-up areas and because the scatter plots suggested that a linear relationship only exists when the building density is not very high (in our dataset the threshold value was about 0.3–0.4, which was calculated as the proportion of land covered with buildings). The correlation values obtained when building heights were taken into account were generally somewhat lower than those obtained without height data.

Overall, the results suggested that the classification of built-up areas into various building density classes might be a feasible approach to refining the classification of built-up areas. Rules for such classification were defined by using the building maps in a subarea. The classification included three classes: 1) *sparsely built-up* (building density > 0, < 0.1), 2) *intermediately built-up* (0.1–0.2), and 3) *densely built-up* (> 0.2). Building heights were not used. All *built-up areas* of the best land use classification result were further classified into the various building density classes (Figure 7). The quality of this classification was evaluated by comparing the results with building densities calculated from the building maps in a validation area. The results were mainly satisfactory. As the building density calculated from the reference maps increased, the building density estimated from the image data also generally increased. However, since building density is a continuous variable, the classes cannot be strictly separated from each other in the imagery.

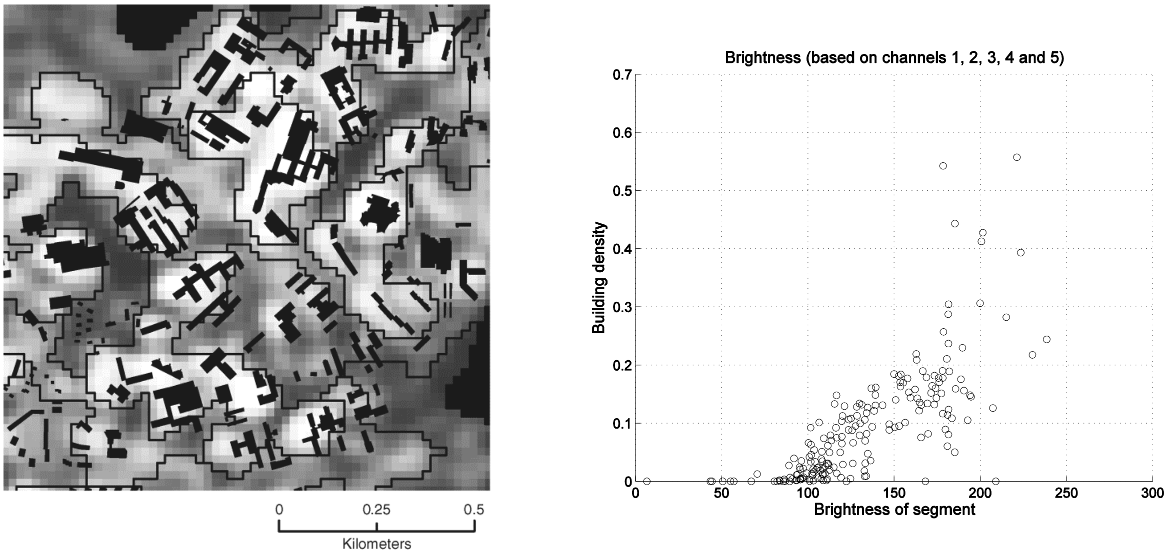

Figure 6. Illustrations of building density calculation. Building polygons overlaid on the segmentation result (left), and scatter plot showing the relationship between the brightness of segments and building density (right). Figures obtained from **I** (buildings © National Land Survey of Finland, 2001; SAR data © M. Engdahl and ESA AO3-277).

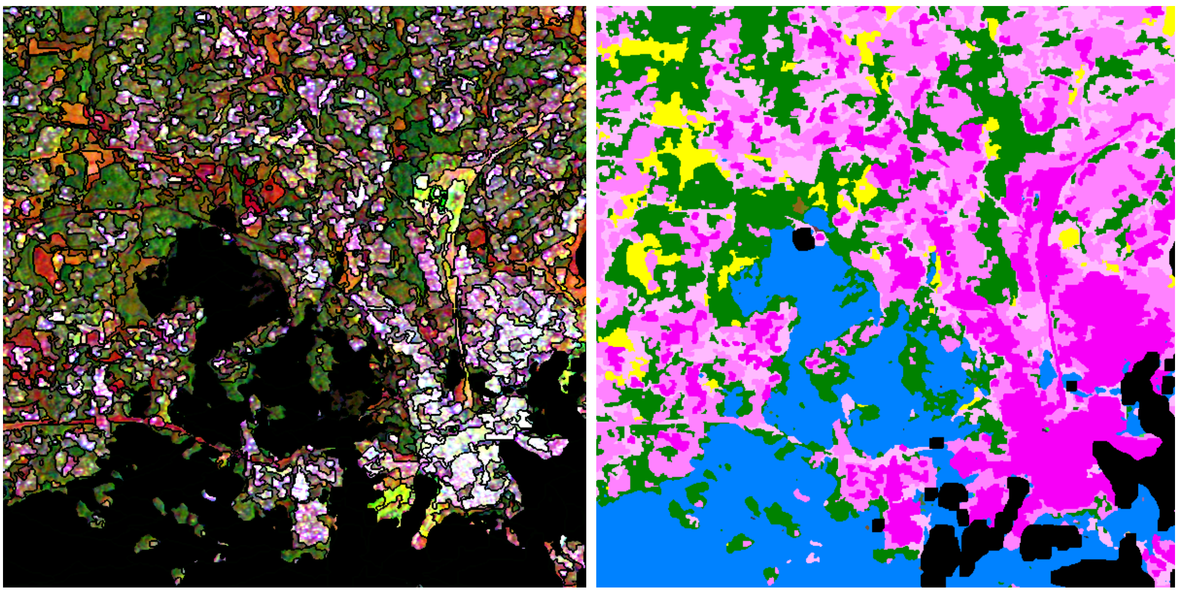

Figure 7. Segments for building density classification overlaid on the multitemporal interferometric SAR image (left), and final land use and building density classification (right). The results are presented for a 12 km × 12 km subarea. Images obtained from **I** (SAR data © M. Engdahl and ESA AO3-277).

4.2 Building detection using laser scanner and aerial image data

Method development

The building detection method developed in the study includes the following basic steps:
1) Segmentation of a raster DSM into homogeneous regions on the basis of height values.
2) Classification of the segments into *ground objects* and *high objects* using preclassified laser points or height differences between the DSM and a DTM.
3) Classification of *high objects* into *buildings* and *trees* on the basis of various attributes derived from laser scanner data and aerial image data (if available).
4) Merging of neighbouring *building* segments to obtain one segment for each *building* and optional postprocessing of the results, especially to eliminate very small *buildings*.

Different versions of the method were used in different papers. The foremost difference between the versions was the approach used for determining rules for the classification of *buildings* and *trees*. Manually defined classification rules were used in the first versions (**II**–**III**). In the latest version, the classification tree method was used to automatically define the rules (a classification tree) and to perform the classification (**IV** and **V**). In both approaches, the definition of the classification rules was based on training segments and various attributes of these training segments. The training segments were defined automatically using up-to-date map data. Some visual checking was also carried out. When the rules were defined manually, suitable attributes were selected, and the rules were defined on the basis of visual analysis of attribute histograms of the training segments. Some classification tests were also carried out. The rules were implemented as fuzzy membership functions. In classification, a membership value for the class *building* was obtained for each segment in addition to the class label. When the classification tree method was used, the method automatically selected the most useful attributes and constructed a classification tree. As an example of a classification tree, the tree used in the building detection tests of **V** is presented in Figure 8. The classification tree rules were used as categorical rules classifying the segments either as *buildings* or *trees*. While the method development for building detection concentrated on buildings, the method also classifies trees as a by-product. All high objects are classified as either *buildings* or *trees* because the large majority of the objects visible in the aerial data used belong to these main classes.

Test results

The building detection method was tested in **II**–**V**. Different datasets, study areas (or outlines of study areas), and versions of the method were used in the individual studies. The results are summarized here at a general level, emphasising important aspects from each study. For a detailed description of the datasets and results, the reader should refer to the original papers.

The first results of the building detection method were presented in **II**. Pixel-based comparison with a reference map showed that the completeness of the detected buildings was 90.0% and the correctness was 85.4%. Building-based accuracy estimation was also carried out. The results showed the dependence of the results on the size of the buildings and the criteria used to consider buildings as being correctly detected. For all buildings, completeness and correctness were 80.3% and 73.1%, respectively, when an overlap of 70% was required between a detected building and a reference building. When only buildings detected with certainty (membership in class *building* ≥ 0.75) were considered in the correctness calculation, the correctness increased to 88.1%. Manually created classification rules were used in **II**. In segmentation and classification, a maximum DSM (maximum height for each pixel) was used. Aerial imagery was not used, but a textural attribute calculated from laser intensity was used in the classification in addition to height texture and a shape attribute.

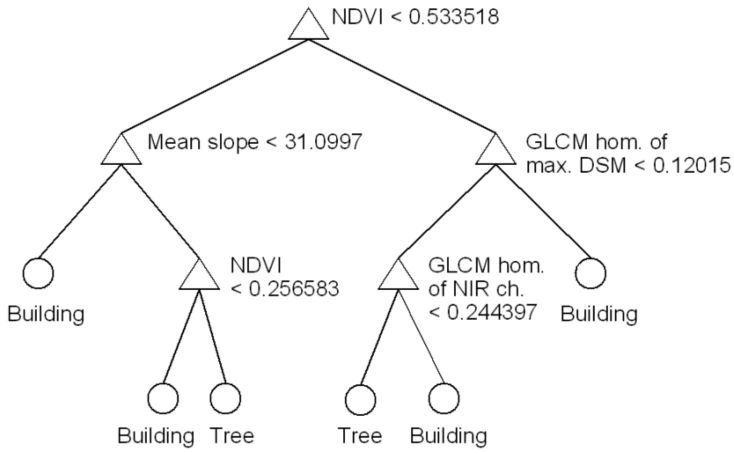

Figure 8. The classification tree used in the building detection tests of **V**. "GLCM hom. of max. DSM" is grey level co-occurrence matrix homogeneity (a texture measure) calculated from the maximum DSM, and "GLCM hom. of NIR ch." is GLCM homogeneity calculated from the NIR channel of the aerial image. Figure obtained from **V**.

Paper **III** provided detailed information on the quality of building detection results when using first pulse or last pulse laser scanner data. Manually created classification rules were then used. The study area and the dataset were different from **II**, and the point density of the laser data was higher. Either a maximum DSM from first pulse data or a minimum DSM from last pulse data was used as the basis for segmentation and classification. An aerial ortho image was also used in the classification stage, but intensity data from laser scanning was not used. Visual and numerical quality evaluations showed that the correctness of the results improved when last pulse data were used instead of first pulse data. According to a pixel-based comparison with a building map, the improvement was about 8 percentage units (from 84.0% to 92.3%). Typical error cases in the first pulse results included the following: vegetation connected to the same segments with buildings and thus classified as *buildings*, buildings not completely detected due to tree cover, and tree segments classified as *buildings*. The area covered by trees was clearly smaller in the last pulse DSM (see Figure 4), which had positive effects on the segmentation and classification results. The number of classification errors in the surroundings of the buildings decreased. The number of false detections also decreased (from about 16% to about 5%). These improvements were clearly shown by a building-based quality evaluation, where the inner part and surrounding area of each reference building was investigated and the number of false detections was calculated. For many buildings, the last pulse data with smaller buildings also corresponded better to the reference map, which improved correctness. The improvement was at its greatest in the low-rise residential area, where the disturbance of vegetation was the greatest and many buildings were smaller on the map than in the DSM due to wide roofs. When last pulse data were used, the completeness of the results decreased by about 2 percentage units according to the pixel-based comparison (from 91.1% to 88.8%). Building-based comparisons also showed that the inner parts of the buildings were more completely detected from first pulse data. One reason for the decrease in completeness was the smaller buildings in the last pulse data. The pixel-based mean accuracy increased by about 3 percentage units (from 87.4% to 90.5%) when last pulse data were used.

The purpose of the building detection tests in **IV** was to test the feasibility of the classification tree method in creating classification rules and to compare the quality of the results to those obtained by using manually created rules. The results produced with manual rules were the same as the last pulse results in **III**, but the reference map and the outlines of the study area were slightly different. The classification tree based approach was applied to the same dataset (last pulse data used). The foremost benefit of the classification tree method appeared to be its high level of automation and speed compared with the process of defining the rules manually. The quality of the results also appeared to be satisfactory. The accuracy was near to that obtained when using the manually created rules. The completeness of the buildings increased by about 2 percentage units, and the correctness and mean accuracy decreased by about 6 and 2 percentage units, respectively. This accuracy estimation was pixel-based.

The final version of the building detection method was thoroughly tested in **V**. The validation areas covered about 4.5 km^2 in total and included more than 1000 buildings ranging from large industrial buildings to small houses and sheds (Figure 9). The point density of the laser data was about 2–4 points/m^2. A minimum DSM was used as the basis for segmentation. A maximum DSM, difference between the DSMs, a slope image, and an aerial ortho image mosaic from digital aerial images were also used as input data for calculating the attributes for the classification of *buildings* and *trees*. The classification tree method was applied to classification (the final classification tree is presented in Figure 8). With all validation areas included, the pixel-based accuracy estimates for buildings were the following: completeness 91.3%, correctness 87.1%, and mean accuracy 89.1%. Building-based completeness and correctness were 88.9% and 86.3%, respectively, when an overlap of 50% between detected and reference buildings was required. An analysis of the building-based accuracy estimates as a function of building size showed that the quality of the results was lowest for small buildings, but the results improved rapidly with increasing building size (Figure 10). When all buildings larger than 60 m^2 were considered, both completeness and correctness were about 96%. Visual analysis of the building detection results revealed that errors occurred typically for special cases that are difficult to interpret correctly. For example, many errors occurred with two-level car parks located on hill slopes and having the upper level on or near ground level on one side. Many of the smallest buildings on the reference map, typically sheds, were very low or covered with trees, and thus difficult to detect. With smaller buildings, some discrepancies between the map and laser and image data also occurred. In the industrial area, for example, there were many sheds, containers or other structures that were detected as *buildings*, but were not presented on the map. Distinguishing such objects from real small buildings is difficult.

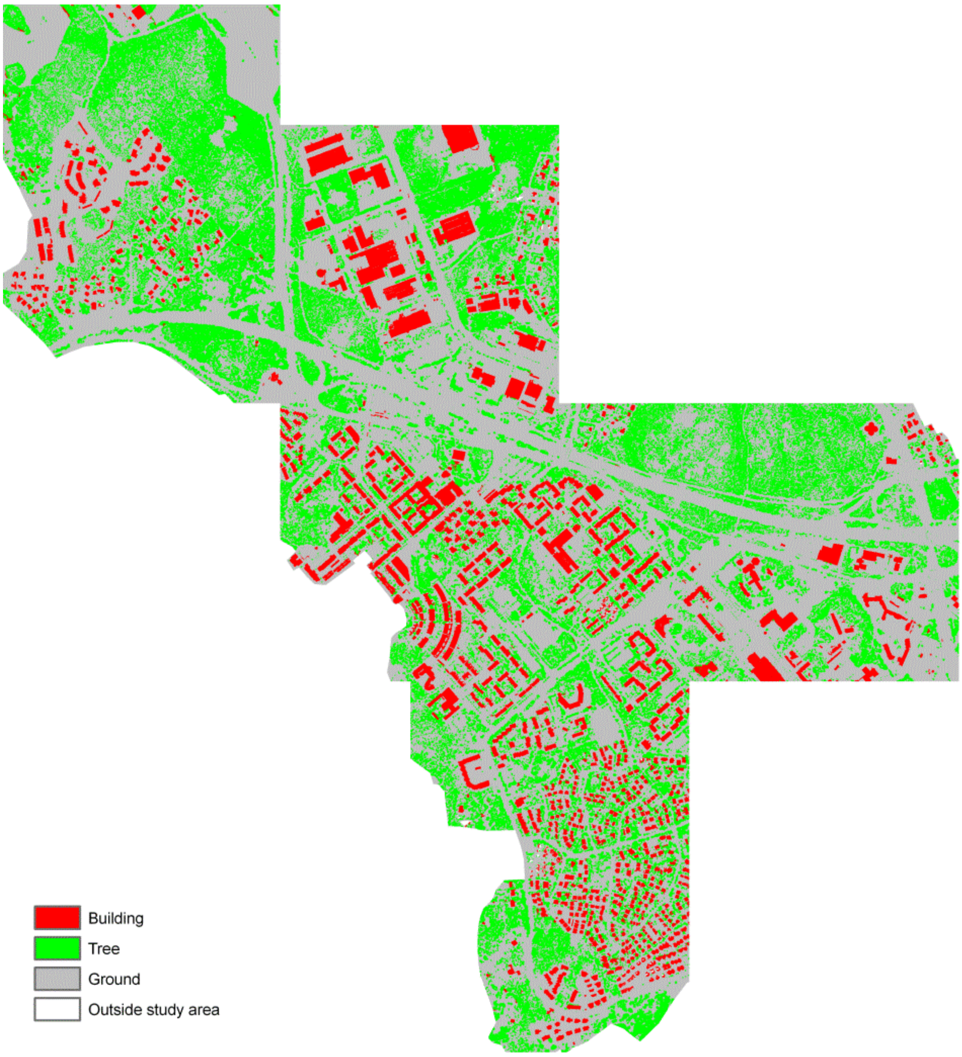

Figure 9. Building detection results (obtained from **V**).

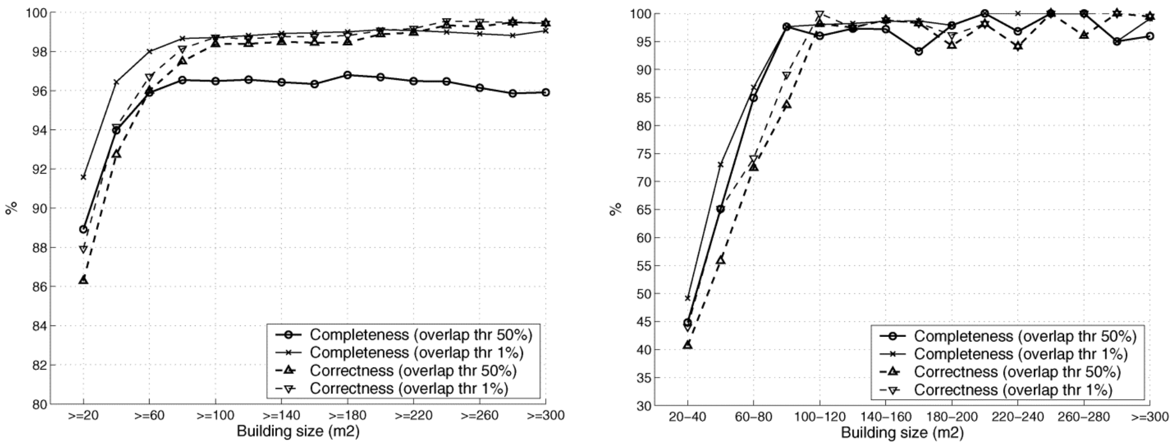

Figure 10. Building-based accuracy estimates for the building detection results as a function of building size (from **V**). Left: Estimates for all buildings larger than the X axis value. Right: Estimates for buildings in the size range given by the X axis values. An overlap of either 50% or 1% between reference and detected buildings was required for a building to be considered as being correctly detected ("thr" is a threshold value).

4.3 Change detection of buildings

Method development

The change detection method developed in the study is based on comparison of the building detection results with an old building map. This approach was selected because multitemporal laser scanner and digital aerial image data are not yet commonly available. The approach could also be well suited for updating existing map databases.

The first version of the method was presented in **II**. It was based on simple analyses of overlaps between building objects in the building detection results and on the map. Matching of the objects was not carried out. Building segments in the building detection results were classified into classes: *new building* (< 10% of the building covered with buildings on the map), *extended building* (10–80%), and *old building* (> 80%). *New* buildings were further divided into two subclasses: *certain detection* and *uncertain detection*. This was based on the membership values of the objects for the class *building* in the building detection stage. Similarly, buildings shown on the old map were divided into the following classes: *detected* (> 80% covered with buildings in the building detection results), *partly detected* (10–80%), and *not detected* (< 10%). The results were visualised as an image showing *new* and *extended* buildings from the building detection results and *old* buildings overlaid on them.

The change detection method was developed further in **V**. The new version includes matching of building objects between the building detection results and the old map, two alternative methods for detecting changed buildings, and some additional rules for cases where misclassifications are likely. Buildings on the map and in the building detection results are still labelled separately, but in such a way that the labels are consistent. This enables the creating of different presentations from the change detection results. For example, *new* and *changed* buildings can be taken from the building detection results, others from the map.

Matching of building objects between those shown on the map and those in the building detection results is based on their overlap and determines the corresponding buildings in the two datasets. Change detection is based on these correspondences. *New* and *demolished* buildings do not have corresponding buildings in the other dataset. If one building on the map corresponds to one in the building detection results, the building is either *unchanged* or *changed*. To determine the class, there are two different alternatives: overlap percentages or a buffer approach. The user can select which of these is to be used and then determine the threshold values. The overlap approach is simply based on a required minimum overlap between the correspondent buildings to consider a building as being *unchanged*. The main idea in the buffer approach is to allow differences near the boundary of a building. If there are more significant differences, the building is classified as *changed*. Buffers are created by using morphological operations. Similar tools have also been utilized in some other change detection studies (Armenakis et al., 2003; Vosselman et al., 2004; Rottensteiner, 2007). Cases where one building in one dataset corresponds to more than one in the other dataset are assigned to class *1-n/n-1*. This can be a real change (e.g., one building demolished, several new buildings constructed), or it can be related to generalization or the inaccuracy of the map or problems in building detection. Additional rules were developed to take into account some typical error cases in change detection: buildings classified as *demolished* or *changed* due to tree cover, and buildings classified as *demolished* due to their low height. The additional rules analyze tree cover or DSM and classify buildings into two special classes if the conditions defined in the rules are satisfied (*assumed to be OK after examining tree cover* or *assumed to be OK after examining DSM*). Examples of change detection results for individual buildings are presented in Figure 11.

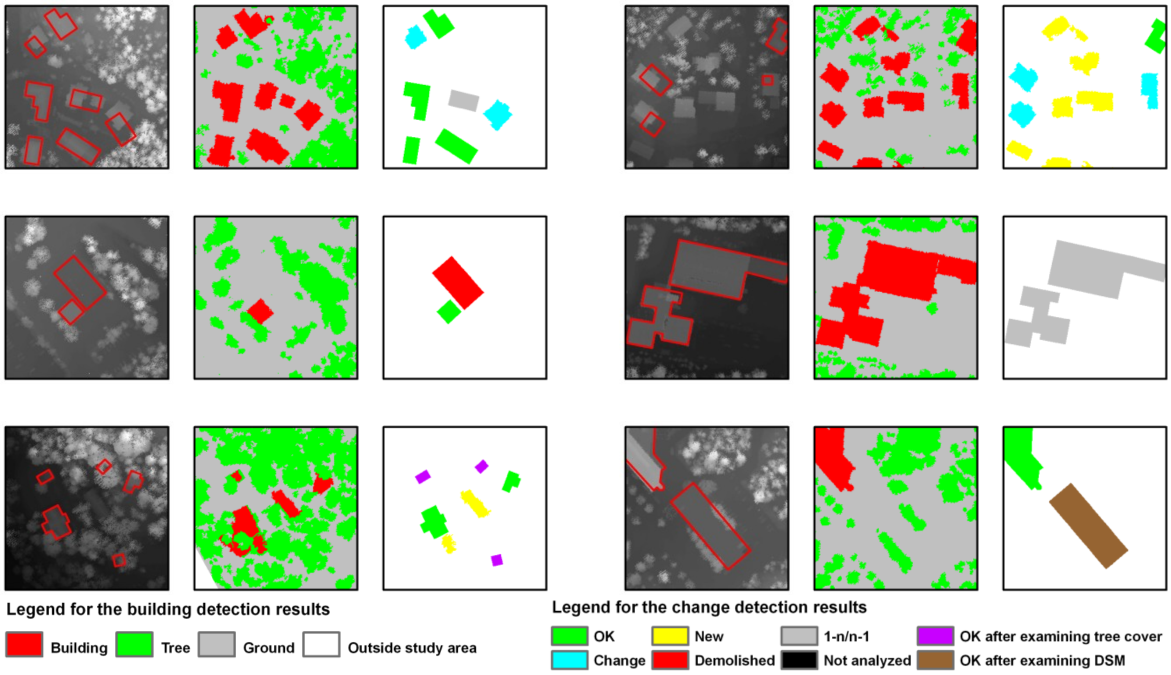

Figure 11. Examples of automated change detection of buildings. The minimum DSM and old building map are presented on the left, the building detection results in the middle, and the change detection results in the right. Figure modified from **V** (buildings of the old map © National Land Survey of Finland, 2001).

Test results

The change detection method was first demonstrated in **II**. To evaluate the quality of the results, some known changes in the study area were analyzed visually. The results were promising. The foremost changes, such as new buildings, had been detected. On the other hand, there were also some problematic cases; for example, buildings classified as *extended* due to small location differences between the two datasets or due to connection of buildings with trees in the segmentation stage. Further development of the method was, thus, considered to be important.

The improved version of the change detection method was thoroughly tested in **V**. Change detection results were compared numerically with reference results (change detection between old and up-to-date building maps) in validation areas covering about 4.5 km^2 and including many real changes. For example, about 250 new buildings had been constructed in the area. Five classes were considered in the quality evaluation: 1) *OK*, 2) *changed*, 3) *new*, 4) *demolished*, 5) *1-n/n-1*. Due to the ambiguous nature of Class 5, the accuracy estimates were calculated with and without this class. Both the overlap and buffer approaches were tested for the detection of *changed* buildings. The completeness and correctness of the change detection results obtained by using the overlap approach and including Class 5 in the accuracy estimation are summarized in Table 4. A building was considered as *changed* if the overlap between the map building and detected building was under 50%.

Table 4. The completeness and correctness of change detection results. All buildings ≥ 20 m^2 included.

Class	Number of buildings in reference results	Completeness	Number of buildings in change detection results	Correctness
1 *OK*	751	85.9%	682	94.6%
2 *Changed*	33	87.9%	53	54.7%
3 *New*	251	68.5%	311	55.3%
4 *Demolished*	33	39.4%	19	68.4%
5 *1-n/n-1*	118	80.5%	181	52.5%
All classes	1186	80.4%	1246	76.6%

Further analysis of the results numerically as a function of building size and visually on the screen provided more information on typical errors. In the case of *new* and *demolished* buildings, errors occurred mainly with small buildings. In the case of *changed* and *1-n/n-1* buildings, errors also occurred with larger buildings. They were related, for example, to connection of buildings with trees or adjacent buildings. The completeness for all *demolished* buildings was only about 39%, but according to a visual inspection these results were misleading because the number of buildings in this class was small, and problematic buildings on the maps had a large impact on the results. When the problematic buildings were excluded, errors occurred with small buildings. Generally, it should be noted that all the numerical accuracy estimates include some uncertainty related to the maps. The uncertainty resulted from some discrepancies and differences in the representation of the buildings when compared with the aerial view.

The effect of the additional rules developed for special cases (*buildings assumed to be OK after examining tree cover* or *DSM*) appeared to be mainly positive. The rule based on the DSM was particularly useful in detecting car parks missed in the building detection stage. A few real changes, however, were missed due to these additional rules. Numerically, the results obtained for *unchanged* and *changed* buildings when using the overlap approach were better than those obtained when using the buffer approach. This was due to the smaller number of changes to detect. The buffer approach is better suited for the detection of subtle changes in the buildings than is the overlap approach.

4.4 Land cover mapping using classification trees, test field points, and various input datasets

Method development

The building detection method presented above (Section 4.2) produces land cover information on buildings and trees from laser scanner and aerial image data. A more general approach regarding both input data and classes was also developed in the study (**IV** and **VI**). The main idea in the approach developed is to combine point-wise reference data with the classification tree method to enable rapid and flexible analysis of different datasets.

The basic assumption in the developed method is that reference points can be used to determine training segments for object-based classification if the points are originally selected inside homogeneous regions. The same reference points can be used with different segmentation results, and each segmentation defines the boundaries of the training segments in that particular case. If a point is inside a segment, it is assumed that the segment belongs to the same class as the point. The use of point-wise data is more flexible than the selection of training segments specifically for each dataset.

The same reference points can also be applied to different data sources if the acquisition time and spatial resolution of the data are compatible with the information content of the points. A permanent and up-to-date land cover classification test field with reference points (Figure 12) could, thus, be useful for rapid analyses of new datasets. The existing points can be used for training and quality evaluation without there being a need to collect separate reference data for each classification study. The test field approach also allows the comparison of classification capabilities of different datasets by using the same training and validation data.

Figure 12. The land cover classification test field used in **VI**. Image obtained from **VI**.

Test results

In **IV**, the classification tree approach was tested for land use classification of high-resolution airborne E-SAR data. The objective was to evaluate the feasibility and quality of the approach when compared with manually created classification rules. The classes under study included *water*, *forest*, *open areas* and *built-up areas*. A set of 87 reference points was used to determine training segments, and another set of 519 reference points was used to estimate the accuracy of the classification. The results were compared with previous classification results of the same dataset (Matikainen et al., 2004). Manually created classification rules had been used in the previous study. Similarly to the building detection tests of **IV** (described in Section 4.2), the land use classification was highly automated and resulted in accuracy that was close to the previous results. The overall accuracy of the classification was 77% whereas manually created rules had resulted in an accuracy of 78%. The mean accuracies of the individual classes were as follows: *water* 58%, *forest* 78%, *open* 84%, *built-up* 58%.

The idea of a permanent land cover classification test field applicable to different datasets was tested in **VI**. In addition to demonstrating the approach, the objective of the study was to compare the land cover classification accuracy achieved with several different high-resolution datasets. These included: 1) digital aerial image data, 2) digital aerial image data and laser scanner data, 3) a high-resolution optical QuickBird satellite image, 4) high-resolution airborne E-SAR data, and 5) E-SAR data and laser scanner data. The aerial image and laser scanner datasets were the same as had been used in building detection and change detection in **V**. The E-SAR dataset was the same that was used in **IV**. The outlines of the study area, however, were different from these papers. The reference points used in Matikainen et al. (2004) and in **IV** for accuracy estimation were updated, and more points were collected. The study area was divided into a training area with 297 points and validation areas with 269 points (Figure 12). The classes studied included *buildings*, *trees*, *vegetated ground* and *non-vegetated ground*. When laser scanner data were used (Tests 2 and 5), *high objects* were first distinguished from the *ground* on the basis of preclassified laser points (the points were classified in TerraScan). *High objects* were then classified into *buildings* and *trees*, and *ground objects* were classified into *vegetated* and *non-vegetated ground* in separate processes by using the classification tree method. Two segmentation levels, one based on the minimum DSM and the other based on the aerial image or E-SAR data, were used. After the classification of *high objects*, a postprocessing operation was also carried out to eliminate very small *buildings* (< 20 m^2).

The results of the land cover classification obtained using aerial image and laser scanner data are shown in Figure 13 for part of the study area. The classification of *high objects* into *buildings* and *trees* and the classification of *ground objects* into *vegetated* and *non-vegetated ground* were based simply on the NDVI because other attributes were not selected by the classification tree method. Compared with the classification of aerial image data alone, the confusion between *buildings* and *non-vegetated ground* could be avoided. Some typical misclassifications, however, were found visually. For example, stretches of narrow roads were misclassified as *vegetated ground* due to obscuring or shadowing trees. Table 5 summarizes the accuracies of all classification tests compared with the validation points.

Figure 13. The land cover classification results obtained using laser scanner and aerial image data. The figure shows a 900 m × 900 m part of the study area used in **VI**.

Table 5. The accuracy of land cover classification results compared with the validation points.

Dataset	**Mean accuracy**				**Overall accuracy**
	Building	***Tree***	***Vegetated ground***	***Non-vegetated ground***	
Aerial ortho image data	62.9%	90.4%	70.2%	74.3%	74.3%
Aerial ortho image data and laser scanner data	96.4%	95.3%	94.4%	98.0%	96.7%
QuickBird image	57.3%	84.6%	65.3%	63.9%	67.3%
E-SAR data	54.5%	69.5%	67.7%	72.7%	68.4%
E-SAR data and laser scanner data	96.4%	95.3%	61.3%	80.3%	82.1%

5. DISCUSSION

5.1 Methods developed for mapping built-up areas

Object-based interpretation methods were developed and tested for coarse land use mapping (**I**), detailed land cover and building mapping (**II–VI**), and change detection of buildings (**II** and **V**) (Figure 14). The methods utilized various modern remotely sensed datasets including aerial laser scanner data, digital aerial image data, multitemporal interferometric SAR data, high-resolution SAR data, and a high-resolution optical satellite image. The interpretation methods consisted of various automatic steps, which either exploited commercial software packages or were based on MATLAB codes written in the study. Visual analysis and manual operations were only needed for method development and supporting tasks: i.e., collection of training and reference data, developing of classification rules, defining input data and parameters for the algorithms, and starting the automatic analysis steps. The methods were different from other studies, although similar tools and ideas have also been used by others as described in the literature review. In **I**, a segment-based approach was applied to the interpretation of a multitemporal interferometric SAR dataset, which was different from previous studies with similar datasets. To the best of the author's knowledge, Paper **II** was the first published study investigating automated change detection between an existing building map and new laser scanner data for the purpose of map updating.

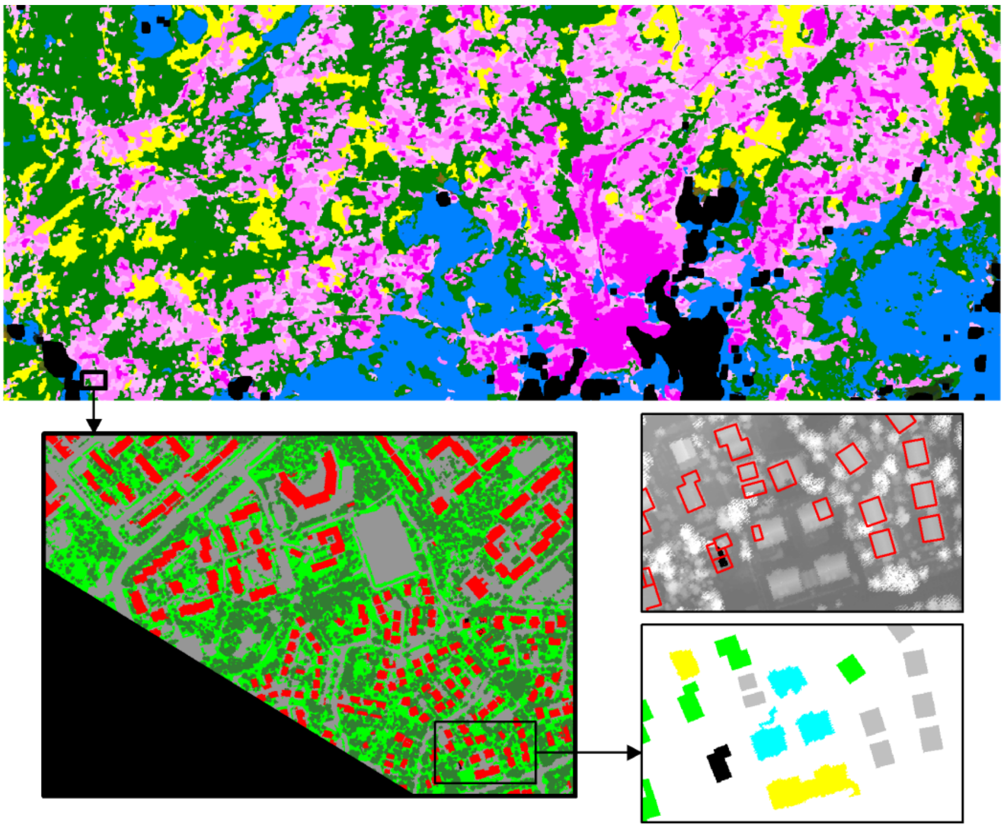

Figure 14. Examples of results from automated interpretation methods developed in the study: coarse land use classification (top), detailed land cover classification (bottom, left), and change detection of buildings (bottom, right). The DSM and old building map used in the change detection are also shown (middle, right). The results are shown for parts of the study areas. Water areas (top) © M. Engdahl. Buildings of the old map © National Land Survey of Finland, 2001.

The use of the classification tree method for building detection and land cover classification (**IV–VI**) significantly increased the level of automation and flexibility of the interpretation processes. The classification tree method has been used increasingly in remote sensing studies in recent years, but at the time of publishing Paper **IV** it had not been widely applied to the analysis of laser scanner data. The benefits of the classification tree method have been discussed by several authors (see, for example, Breiman et al., 1984; Safavian and Landgrebe, 1991; Hansen et al., 1996; Friedl and Brodley, 1997; Lawrence and Wright, 2001; Thomas et al., 2003; Huang and Lees, 2004; Lawrence et al., 2004). From our point of view, the method proved to be well suited for the type of object-based and rule-based classifications we were interested in. A large number of different attributes can be presented to the method as input data, and it automatically selects the most useful ones. In this it differs from most automatic classification approaches, which require that the user must select suitable attributes before classification. The method can also use different attributes for distinguishing different classes. The structure of the classification tree is easy to understand, and it provides information on the usefulness of the different attributes in the classification task, although caution is needed in interpreting this information (see Breiman et al., 1984). The main benefit of the classification tree classification in our study was its high level of automation. Once the scripts had been created and the input data were in the correct format, the tree could be created and the classification could be carried out in seconds. The classification step itself is also fast when using manually defined classification rules, but the development of the rules is time-consuming. The development work, including different analyses and experiments to find a good classification process and rules for a new application, may well take weeks or at least days. It should also be noted that the same rules are not directly applicable to different datasets. With an automatic approach, new rule sets can be defined easily. If needed, manually defined rules can be added in the interpretation process.

Steps were also taken in the study to automate the acquisition of the training data. Map data were used to automatically define training segments in the building detection studies (visual checking was also used). Training areas derived from map data have also been used by other authors (e.g., Knudsen and Olsen, 2002, 2003). The idea of using a permanent land cover classification test field together with the classification tree method was introduced and tested in **IV** and **VI**. This approach enables the user to define training segments automatically for various different datasets and to compare the classification capabilities of the datasets by using the same validation data.

5.2 Quality of the results

As described in Section 4, the quality of the interpretation results was tested carefully by using validation data that were separate from the training data. The results provided new information on the following topics:

- The quality of object-based land use classification using a multitemporal interferometric SAR dataset.
- The applicability of the interferometric SAR dataset for the mapping of different types of built-up areas.
- The quality of automated building detection using laser scanner and aerial image data.
- The quality of automated change detection between an old building map and building detection results obtained using laser scanner and aerial image data.
- The relative performance of first pulse and last pulse laser scanner data for automated building detection.

- The relative performance of the classification tree method and manually created classification rules for automated building detection and land cover classification.
- The relative quality of land cover classification results obtained using various high-resolution datasets.

The land use classification results obtained using the interferometric SAR dataset (**I**) were clearly better than those obtained in some previous studies with interferometric data, especially for built-up areas (see, for example, Strozzi et al., 2000). It should be noted, however, that direct comparison of classifications with different datasets, class definitions, and number of classes is impossible. The main explanation for the good accuracy achieved in our study was probably the high quality of the interferometric dataset. Engdahl and Hyyppä (2003) also achieved good classification results when applying an unsupervised pixel-based classification to the same dataset (due to different classes, direct comparison is difficult). The object-based approach applied in the present study, however, had some benefits when compared with pixel-based classification applied in previous studies. In particular, the classification process was highly automatic, and visually good results with homogeneous regions were obtained without any postprocessing. Built-up areas from the land use classification results were also further analyzed and classified in object-based form. Low-rise areas, high-rise areas and industrial areas of Finnish topographic maps appeared to be difficult to distinguish from each other, but correlations between the building density of an area and its intensity and coherence in the image data were found. As regards intensity, this result was in accordance with Dong et al. (1997), who suggested that a good correlation between the backscattering response and the bulk size and density of buildings could be found if the effect of the buildings' orientation is compensated. In our study, however, such compensation was not carried out.

Automated detection of buildings from laser scanner data or laser scanner and aerial image data was tested in **II**–**V**. The pixel-based accuracy estimates for the building detection results were 84–95%. Values of an approximately similar level have also been reported by other authors (e.g., Rottensteiner et al., 2007; Rutzinger et al., 2009). Real map data were used as reference data in our study, and the results thus provide realistic information on the performance of the method compared with current map data. In most of our studies, the reference maps were based on the city base map, which is a large-scale and detailed topographic map used for purposes such as city planning. We estimated the positional accuracy of buildings to be 0.5 m or better on the map. However, it is very important to note that buildings appear different on the maps and in remotely sensed data. An obvious difference, in addition to generalization, is that the maps represent the bases of the buildings instead of roof edges. A 100% correspondence between building detection results and map data would thus not be reached in a pixel-based comparison even if the detection process worked perfectly. Especially in low-rise residential areas, buildings are often larger in the laser and image data than on the map due to wide eaves. The building-based accuracy estimates are more tolerant of differences between the map and remotely sensed data, as well as of errors in the shape of the detected buildings, than the pixel-based estimates. On the other hand, the estimates are dependent on the criteria used to determine which buildings are correctly detected (overlap percentages in our case), and they are also dependent on the size distribution of buildings in the area (see Rutzinger et al., 2009). Results obtained in our studies were good, except for the smallest buildings. Lower accuracy when dealing with small buildings is natural and this has also been noticed in other studies (Zhan et al., 2005; Rottensteiner et al., 2007; Rutzinger et al., 2009). The results of **III** confirmed the benefits of using last pulse instead of first pulse data as the main data source for building detection. Before our study, detailed numerical quality analyses on the topic were not available. The building-detection and land cover classification experiments in **IV** showed that the classification accuracy obtained with the classification tree method was almost on the same level as the accuracy achieved in our previous studies with manually created rules.

A method for change detection between the building detection results and an old map was developed and tested in **II** and **V**. The method is object-based and analyzes individual building objects (using input data in raster format). Buildings are classified into classes: *OK*, *changed*, *new*, *demolished*, *1-n/n-1*. In **V**, the results were compared with an extensive reference dataset representing real changes. This type of information was not widely available from previous studies with similar datasets. The results were satisfactory, taking into consideration that there was also some uncertainty related to the maps (some discrepancies and differences in the representation of the buildings when compared with the aerial view). In particular, real changes were found relatively well. The main problem was false detection of changes, especially *new*, *changed*, and *1-n/n-1* buildings. The total number of false changes, however, was moderate: 18% of all buildings in the change detection results were assigned to some of the change classes, although they were *unchanged* or not detected as *new* buildings in the reference results. The trend that completeness in detecting changes was higher than correctness was similar to that found in many other change detection studies (e.g., Holland et al., 2008; Champion, 2009). Completeness in detecting changes is also more important than correctness if the updating continues manually. A moderate number of false detections can be checked visually and bypassed, but finding missing changes is time-consuming and can defeat the object of using an automated method.

Paper **VI** demonstrated the application of the classification tree method and permanent test field points for a land cover classification study and provided information on the quality of various data sources for detailed land cover mapping in a suburban area. To the author's knowledge, the capability of such datasets for land cover classification had not been previously tested in one study area. The results clearly showed the benefits of using laser scanner data. The highest overall accuracy (97%) was obtained when aerial image and laser scanner data were used. The results for the aerial image classifications, with and without laser scanner data, were in accordance with those obtained in previous studies (e.g., Sanchez Hernandez et al., 2007; Huang et al., 2008). The combination of laser scanner and E-SAR data also gave good results (82%). In this case, however, the classification of *buildings* and *trees* was, in fact, based on the laser scanner data alone because the classification tree method did not select any rules based on SAR data for this classification step. The lowest accuracies were obtained for the QuickBird and E-SAR classifications (67% and 68%, respectively). An important reason for this result was the lower spatial resolution of these datasets compared with the aerial image and laser scanner data. For example, there was clearly more detail in the aerial image classification results than in the QuickBird results. The accuracy estimation of the classification results was based on 269 validation points located within homogeneous regions. To evaluate the adequacy of the validation points for the comparison purposes of the study, preliminary analyses with raster maps created from building vectors and road centre line vectors were also carried out. A comparison of the results with the map data confirmed that the best results were clearly obtained in the classifications using laser scanner data. It should be noted, however, that the exact numerical accuracy estimates are likely to change if map data are used as reference data.

In **VI**, the overall accuracy of the E-SAR classification was lower (68%) than in **IV** (77%). This can be related to the different reference points used for training and to the different classes of interest. In **IV**, the SAR imagery was used to define training points, which ensured that the points were correctly located. For example, a check was performed to ensure that building points were located on buildings both in the SAR and in the aerial image data. The classes were *water*, *forest*, *built-up*, and *open*, which included both vegetated and non-vegetated areas. In **VI**, the training points collected from aerial imagery were used in each classification test. The classes included *buildings*, *trees*, *vegetated ground*, and *non-vegetated ground*. Due to the side-looking geometry of the SAR sensor, buildings in the SAR images get to be slightly shifted from their real positions, which can cause some discrepancies between the SAR data and the reference points. A general limitation of the permanent test field approach is that the same points are not necessarily equally well suited for the analysis of different datasets with different spatial resolutions, geometric characteristics, and acquisition dates. Therefore, the results for individual datasets can be less optimal than in studies where the reference data are specifically collected for each dataset. The approach is best suited for rapid analyses of new datasets to obtain a general idea on their capability for land cover classification.

5.3 Feasibility of the methods for practical mapping applications

As described in Section 4, promising results were obtained in land use/land cover classification, building detection, and change detection of buildings. It thus seems likely that automated, object-based interpretation methods applied to modern-day, remotely sensed datasets could also produce useful results for practical mapping applications. Basically, classifications of detailed laser scanner and aerial image datasets could be used in the mapping of topographic objects and in detailed land cover monitoring. Classifications of the coarser image datasets, i.e., interferometric ERS data, E-SAR data, QuickBird image, or other similar data, could be applied to coarser land cover monitoring applications and possibly to small-scale topographic mapping. The interferometric ERS data appeared to be feasible for the mapping of built-up areas as large entities and for further analysis of the building density of the areas if the building density is not very high (in our dataset, the threshold value was about 0.3–0.4, calculated as the proportion of land covered by buildings). The classification of high-resolution SAR data and multispectral optical satellite data can provide information on smaller details inside built-up areas (buildings, trees, vegetated and non-vegetated areas), but it seems obvious that the quality of the results achieved in our study would not be high enough for topographic mapping purposes in Finland and other countries where accurate topographic maps are available. It should be noted, however, that the spatial resolution of multispectral optical satellite image data can be improved by using pansharpening techniques, which were not used in our study. These techniques increase the information content of the images for topographic mapping (Topan et al., 2009). Optical satellite image data can also be combined with height data from laser scanning or from image-based techniques, and this is likely to lead to improved results (e.g., Chen et al., 2009).

Considering topographic mapping, the performance of automated building detection and change detection of buildings is particularly interesting. If the quality of the results is high enough, these could be used as aids in manual mapping and updating processes to avoid the need for visual searching for new buildings and checking of all old ones. These methods do not provide the exact boundaries of the buildings, and it is assumed in the following that a human operator would still be needed for checking the automatically produced results and for delineating the boundaries. As another alternative, further automation of the mapping process would also be possible. Automatically detected buildings could be used as the basis for automated boundary delineation and 3D modelling of buildings.

The quality requirements of the Finnish Topographic Database allow four errors per 100 buildings (missing or additional buildings) (Maanmittauslaitos, 1995), which corresponds to a building-based accuracy level of 96%. In the building detection tests of **V**, completeness and correctness values of about 96% were reached when all buildings larger than 60 m^2 were included in the analysis. When smaller buildings were also considered, the accuracy was lower. These results suggest that if automatically detected buildings were used as the basis for manual building mapping and if the operator's task was only to delineate the detected buildings, the quality of the resulting map would be close to the operational requirements. It should be noted that most buildings are clearly larger than 60 m^2, the smallest buildings (e.g., sheds) are often less important, and the city base map used as reference data in our study included more small buildings than the Topographic Database. It could also be easy for an operator to insert some of the missing buildings, and still avoid doing a visual examination of the entire area. On the other hand, it should be noted that some building roofs have low reflectance in the laser scanner data and such buildings can be effectively missing from the data. In our study, map buildings including missing laser scanner data were excluded from the completeness analysis. In an operational process, areas with such buildings would require additional checking.

The change detection results of our study (**V**) included five classes, four of them indicating some change in the buildings compared with the map (*changed*, *new*, *demolished*, *1-n/n-1*). It was found that 9% of all reference buildings belonged to a change class in the reference results but were labelled as *unchanged* or not detected as a *new* building in the change detection results. These buildings would remain uncorrected in the update, assuming that the operator would check and correct buildings assigned to the change classes. The percentage is a little higher than the 4% allowed in the quality requirements of the Topographic Database (missing and additional buildings), but it includes many small buildings not necessarily shown in the Topographic Database, some *changed* and *1-n/n-1* buildings, and it is affected by the uncertainty of the reference data (e.g., *demolished* buildings that had not really been demolished). It should be noted that these results were obtained by using the overlap approach with a threshold value of 50% to distinguish *unchanged* and *changed* buildings from each other. This setting is suitable for detecting significant changes in the existing buildings. The quality of *changed* buildings with respect to operational requirements was not investigated in the study. If there is a need to detect more subtle changes in buildings, the buffer approach might be a better choice than the overlap approach. On the other hand, the basic idea of carrying out change detection after building detection is probably most effective when the goal is only to detect major changes. In order to detect subtle changes in the shape of the buildings, it would be better to first carry out the building extraction process further, i.e., to determine the exact boundaries of the buildings.

The land cover classification results obtained using laser scanner and aerial image data (**VI**) could also yield useful information on the location of forested areas and roads, especially for mapping forested areas and for updating of road databases. Forested areas have not been delineated as objects on Finnish topographic maps. Automated classification of laser scanner and aerial image data could be utilized for mapping them. Such a process is used in the production of a topographic landscape model (Schmassmann and Bovier, 2010) in Switzerland. Roads were not separated from other non-vegetated ground objects in our study, but they are easy to recognize visually from the results, except for the narrowest ones. Useful information on new and no longer existing roads might thus be obtained by comparing the results visually with existing map data.

It should be noted that the properties and acquisition times of the laser scanner and aerial image data in our study did not correspond to those used in topographic mapping in

Finland. At the time of acquiring the datasets used in **V** and **VI**, the trees were in full leaf. Normally, both laser scanner and aerial image data are acquired early in spring when deciduous trees are not yet in leaf. The early acquisition time is the best for accurate mapping of objects such as buildings and roads, but it is not ideal for the classification of vegetated and non-vegetated objects. The point density of laser scanner data and the spatial resolution of aerial imagery are normally somewhat lower than in our study. There is some evidence indicating that satisfactory building detection results can be obtained with our method if sparser laser scanner data are used (Kareinen, 2008), but further tests are needed. In the future, the point density of laser scanner data is likely to increase as a result of technical development.

5.4 Other studies and developments

Many of the topics investigated in our study have also been investigated in numerous other studies during the recent years. As is already described in Section 2, particularly building detection, change detection, and land cover classification using laser scanner and aerial image data have been topics of active research. New methods and studies related to these topics are being published constantly. The most recent studies include, for example, the use of full-waveform laser scanner data (Mallet et al., 2008; Alexander et al., 2011; Guo et al., 2011). Compared with conventional laser scanner data, full-waveform data offer new and potentially useful features for classification applications. Coherence and intensity data from interferometric SAR data have been recently used in land cover classification or in change detection, for example, by Santoro et al. (2007), Del Frate et al. (2008), Liao et al. (2008), and Pratola et al. (2011). Pratola et al. (2011) used COSMO-Skymed images with spatial resolutions of about 1 m and 3 m. The potential of new, high-resolution SAR systems, such as TerraSAR-X and COSMO-Skymed, for providing interferometric data has been discussed, for example, by Bamler et al. (2009) and Eineder et al. (2009). Interferometric data from these sensors can even be used for the analysis of individual buildings. Dell'Acqua et al. (2009) discussed the use of height data (DSMs) derived from interferometric SAR images as one data source for rapid mapping. Polarimetric interferometric data have also been used for land cover classification (e.g., Li et al., 2010).

New change detection methods for buildings have recently been developed, for example, by Chen and Lin (2010), Chen et al. (2012) and Chaabouni-Chouayakh and Reinartz (2011). Chen and Lin (2010) and Chen et al. (2012) used laser scanner and aerial image data to detect changes in 3D building models. Chaabouni-Chouayakh and Reinartz (2011) used multitemporal DSMs derived from aerial or satellite imagery. Other studies concentrating on change detection or updating of buildings from satellite imagery have also been published (e.g., Champion et al., 2010; Poulain et al., 2011; Doxani et al., 2012). Leignel et al. (2010) discussed possible methods for change detection at regional and local scales with the aim of assisting in the updating of topographic databases. Fortier et al. (2011) tested the use of temporally invariant calibration sites to classify satellite images. The idea of utilizing the same calibration and validation data for the classification of various different images was somewhat similar to our land cover classification test field, but in their study the interest was in the classification of old images instead of new ones.

Classification trees and further developments of the approach, such as boosting and random forests (Bauer and Kohavi, 1999; Breiman, 2001), have become popular (e.g., Lawrence et al., 2004; Zingaretti et al., 2007; Chehata et al., 2009; Mancini et al., 2009; Alexander et al., 2011; Fortier et al., 2011; Guo et al., 2011; Salah et al., 2011). Generally, the need for efficient automatic feature selection approaches in object-based image analysis has received attention in recent studies (e.g., Novack et al., 2011; Laliberte et al., 2012). According to Trimble Geospatial (2012b), classification trees have also been included in the latest eCognition version. In some cases, however, good classification results can also be achieved with simple methods and a small number of features. In the building detection study by Hermosilla et al. (2011), a method based on nDSM and NDVI thresholding and some postprocessing gave better results than an object-based classification approach using decision trees.

During the past few years, there have also been significant changes in operational mapping work. As is discussed in Section 1.1., airborne laser scanning and digital aerial images are now used operationally. The practical significance of automated analysis methods for these datasets has thus increased significantly. Software tools have also developed during the past years. As one example of this development, commercial tools are available for classifying building points from laser scanner data and for using them to automatically derive rough 3D models of buildings for large areas (Soininen, 2010). Automated change detection methods are not yet widely applied in practice, but there is great interest in the topic (Holland, 2010).

5.5 Further research

The study has raised several topics for further research and development. Basically, these are related to the improvement and expansion of developed methods, to the optimal use of current and new datasets, and to the advancement of the practical exploitation of automated interpretation methods.

To achieve improvements in building detection and change detection of buildings, further studies should concentrate on aspects that have arisen as being problematic, such as low buildings in sloping terrain (e.g., car parks), buildings under trees, buildings connected with trees, and buildings with vegetation growing on their roofs. In our study, improvement was already achieved in the change detection step by developing additional rules for analyzing some of these cases. If map data are available, they can be used to support interpretation (e.g., Rottensteiner, 2007; Holland et al., 2008). Caution is needed, however, not to rely too much on map data because changes between the map and new remotely sensed data should be found. Classification of other objects, such as roads, in addition to buildings and trees could decrease the number of false detections of buildings. This has also been suggested by others (Knudsen and Olsen, 2002; Champion, 2009). Improvements may also be achieved by more advanced use of aerial image and laser scanner data in the process. For example, connections between buildings and adjacent trees could possibly be diminished by further analysis of aerial image data (e.g., Lee et al., 2008) or of the original laser points for the detected buildings. Change detection methods based on multitemporal data can be developed in the future when both old and new laser scanner and digital aerial image datasets are available.

The classification tree method and permanent test field points provided a feasible means of carrying out land cover classification of various datasets and of providing a general idea of the relative quality and potential of the datasets. This approach could be further developed and exploited by creating new test fields applicable for a wider range of different datasets. In particular, different spatial resolutions and classes of interest should be taken into account. As has already been mentioned, further developments of the basic classification tree method are available. It would be useful to test whether these more advanced classification approaches increase the accuracy of the classification results. Other classification methods could also be tested. Future research topics related to land cover classification should also include optimal combination of different optical and SAR datasets and more detailed classifications (including more classes).

From the practical point of view, further research is needed on the validity of the interpretation results and optimization of various parameter values. In the study using the multitemporal interferometric SAR dataset, the dataset was based on a large number of interferometric image pairs (14). It would be useful to test how the number of images affects the quality of the results. In the case of laser scanner data and digital aerial images, the effects of spatial resolution and acquisition time of the data on the results should be studied. The acquisition frequency of the datasets should also be taken into account. For example, aerial images covering the whole of Finland are acquired once every few years, but the interval between surveys for acquiring laser scanner data is longer than this. If up-to-date laser scanner data are not available, height data, which have clearly proved to be useful in classification, could be produced automatically from aerial images by using photogrammetric image matching techniques. Operational requirements should be considered in setting the parameters for the methods, for example, for change detection of buildings. Another topic requiring further study before automated methods can be put into practice is the applicability of the classification rules in different areas. The classification rules created for building detection or land cover classification in one area can be utilized in other similar areas if the data have similar characteristics. Changes in the data or characteristics of the areas, however, require changes in the rules. Basically, new sets of rules could be created automatically by using the classification tree method and up-to-date map data of training areas or up-to-date test field points. Several training areas or test fields may be needed to create feasible rules for large areas, such as an entire country.

Work is also needed for automated interpretation methods to be fitted in with operational mapping processes and to carry out extensive practical tests to determine whether they are useful and accurate enough for operational mapping work (e.g., Holland et al., 2008). Ideally, the use of such methods could lead to significant savings in time and costs in the collecting of map data and updating of databases. Comparisons of quality between current processes and new alternatives provided by automated methods would also be important. The results of automated interpretation are not 100% correct, but errors and deficiencies also occur in connection with manual methods. When assessing the usefulness of automated change detection, it should also be noted that even if some changes are missed by an automated method, the database resulting from updating will be more accurate than the version before updating. If the updating process can be made faster and easier, this can also have positive effects on the quality of the data available to users.

Our study concentrated on buildings and on land use/land cover classification with a few classes. Similar methods, however, can be developed for other map objects and applied to wider sets of land cover classes. The basic tools used in the study, such as image segmentation, the classification tree method and the permanent test field approach, can also be applied to other objects and classes. Object-specific development work, however, is also needed. For example, to develop change detection methods for roads, forested areas, and fields, the specific characteristics of these objects should be taken into account.

New and interesting datasets not used in our study include full-waveform laser scanner data and hyperspectral image data from aerial sensors. These could provide useful information for detailed classification of different objects. The potential of current and future high-resolution optical and SAR satellite images is also worth studying, especially for land cover classification. Some improvements in aerial image classification could be achieved by using radiometrically calibrated imagery (Honkavaara et al., 2011). Radiometric calibration of laser scanner intensity has also developed during the past years (e.g., Wagner, 2010), and this increases the value of the intensity data for classification applications. The combination of aerial data with terrestrial data acquired by means of mobile mapping methods opens up new possibilities for the mapping of built-up areas.

With such a wide range of potentially useful datasets, it is a challenging task to find the most effective way of utilizing them in the various mapping tasks.

6. SUMMARY AND CONCLUSIONS

The basic hypothesis in this study was that highly automated classification and change detection methods can be developed for mapping and map updating by applying object-based interpretation approaches and new remotely sensed datasets, and that these methods can produce high-quality results. To test the hypothesis, the objectives of the study included the development of object-based interpretation methods for coarse land use mapping, detailed land cover and building mapping and change detection of buildings, and testing the quality of the methods. Object-based interpretation methods were developed for:

- Mapping built-up areas using a multitemporal interferometric SAR dataset,
- Building detection using laser scanner and aerial image data,
- Change detection of buildings using the building detection results and an old building map, and
- Land cover mapping using classification trees, test field points, and various input datasets.

The interpretation methods developed in the study consisted of various automatic steps. Visual analysis and manual operations were only needed for method development and supporting tasks. An important part of the study was the application of the classification tree method to building detection and land cover classification to automate the development of classification rules. This approach lead to considerable time-savings when compared with the conventional approach of using manually defined classification rules in object-based classification. The idea of using a permanent land cover classification test field together with the classification tree method was presented and tested in the study to allow rapid testing and comparison of new datasets. Test field points can be used to define training segments automatically for various different datasets and to test the quality of the interpretation results.

As regards the quality of the interpretation methods, the main results of the study are listed as follows:

- Coarse land use classification of the multitemporal interferometric SAR dataset into *built-up areas*, *forests*, and *open areas* lead to an overall accuracy of 97% when compared with a set of reference points. Compared with a reference map, the accuracy was 86%.
- Low-rise areas, high-rise areas, and industrial areas as shown on Finnish topographic maps were difficult to distinguish from each other when using the interferometric dataset. On the other hand, a correlation between the building density of an area and its intensity and coherence in the image data was found, and the dataset appeared to be promising for classifying built-up areas into subclasses according to building density.
- Building detection was tested by using different laser scanner and aerial image datasets. The completeness and correctness of the building detection results were 84–95% when compared with up-to-date map data pixel-by-pixel. In the most extensive test in the Espoonlahti area, completeness was 91% and correctness was 87%. These pixel-based accuracy estimates are affected by differences in the appearance of buildings between maps and the aerial view. Building-based completeness and correctness, which consider entire buildings and are more tolerant of small differences, were 89% and 86%, respectively, when all buildings larger than 20 m^2 were included in the analysis. These values increased to about 96% when all buildings larger than 60 m^2 were considered. This accuracy level (96%) is compatible with the quality requirements of the Finnish Topographic Database when considering missing and additional buildings.

- The study also included a comparison between first pulse and last pulse laser scanner data in building detection. The results showed that the use of last pulse instead of first pulse data can improve the results of automated building detection, especially by decreasing the number of classification errors in the surroundings of the buildings and the number of false detections. According to a pixel-based comparison with a building map, the correctness of the results improved by about 8 percentage units and the completeness of the results decreased by about 2 percentage units. An important reason for the differences is the smaller proportion of vegetation in the last pulse data. The smaller buildings in the last pulse data also affect the results.
- The quality of the change detection results for buildings was tested by using two real building maps (old and new maps). In change detection, buildings were divided into five classes: *OK*, *changed*, *new*, *demolished*, *1-n/n-1*. Considering the five classes and all buildings larger than 20 m^2, the completeness and correctness of the results were 80% and 77%, respectively. In the case of *new* and *demolished* buildings, errors occurred mainly in small buildings. It was found that 9% of all reference buildings belonged to a change class in the reference results, but not in the change detection results. These buildings would remain uncorrected in the update, assuming that only buildings assigned to some of the change classes would be considered. It should be noted, however, that the dataset used in the study included many small buildings that are normally presented on city base maps, but not in the Topographic Database, for example, and there was also some uncertainty related to the reference data.
- Land cover classification performance of different high-resolution datasets was compared by using the classification tree method and permanent test field points. The best results were obtained by using laser scanner and digital aerial image data. The overall accuracy of this classification was 97% when compared with reference points. The classes included *buildings*, *trees*, *vegetated ground* and *non-vegetated ground*. The overall accuracies of the other classifications were as follows: 74% for digital aerial image data, 67% for QuickBird satellite image, 68% for high-resolution airborne E-SAR data, and 82% for E-SAR data and laser scanner data.
- Building detection and land use classification results obtained by using the classification tree method were compared with the results obtained in previous studies by using manually created classification rules. The accuracy was almost on the same level. The mean accuracy of buildings was about 2 percentage units lower, and the overall accuracy of the land use classification results was about 1 percentage unit lower than in the previous results.
- The object-based classifications resulted in homogeneous regions and thus provided results that were visually generally good and also resembled maps drawn by human operators.

The results obtained in the study thus confirmed the initial hypothesis of the study. It seems that object-based interpretation methods applied to new remotely sensed datasets have high potential for various mapping applications ranging from coarse land use mapping to the detection of changes in individual objects. In particular, the combination of laser scanner data and digital aerial imagery provides good input data for topographic mapping. The methods investigated in the study do not yield the exact boundaries of buildings or other objects, but they could be helpful in the manual updating process to avoid the need for visual checking of all existing objects and searching for new objects. Automatically detected buildings could also be used as the basis for further automated boundary delineation and 3D modelling of buildings. Land cover classifications produced from laser scanner and aerial image data could also provide useful information for mapping forested areas and updating of road databases. The other datasets, i.e., SAR and optical satellite data, used in the study have their main potential in land cover monitoring applications.

Further research should consider more advanced interpretation methods, new and multitemporal datasets, optimal combinations of the datasets, and wider sets of objects and classes. From the practical point of view, work is needed to fit automated interpretation methods in operational mapping processes, to optimize various parameter values and to test the validity and usefulness of the results in the processing of large areas.

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