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Urban structuring using multisensoral remote sensing data

By the example of the German cities Cologne and Dresden

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***Abstract*—The urban landscape is a highly complex and small-structured, heterogeneous area as a result of permanent human settlement. Urban structure is scale-dependant and can be expressed on various levels of detail by satellite imagery. Very high resolution satellite (VHR) sensors are capable of mapping and monitoring cities - on house/block level - with their high degree of landcover diversity. However, detection of morphological features such as shape and elevation of single objects is performed much better when a digital surface model (DSM) – e.g. derived by airborne laserscanning - is incorporated. An object-oriented methodology for the joint analysis of optical satellite data and a digital surface model is presented for the classification of the urban morphology in terms of urban structural types. These are spatial units – mostly on block level – with aggregated information on the classified single features like landcover/landuse and urban fabric. Hence, a hierarchical, modular segmentation and classification workflow is implemented to extract the required information. The methodology is applied on two study areas in the cities of Cologne and Dresden, Germany, and a validation of the capability of the potential for transferability of the rulebase is shown.**

I. INTRODUCTION

The shape of a city is the most visible result of the driving forces of urban development (economy, society/culture, and environment). Therefore, the urban spatial structure is a physical reflection of various processes during the evolution of a city and its characterisation is valuable source of information [1]. Over the past decades, urbanisation processes have caused rapid developments and today more than half of the world's population live in cities [2]. Against this background, area-wide and up-to-date spatial information of urban areas is in demand.

Remote sensing data meet these requirements and are capable of providing crucial information for city planners [3]. The technical development of the latest generation of VHR optical satellite-based sensors - such as *Ikonos, Quickbird, GeoEye-1, WorldView-1 and SPOT 5* - has led to highly detailed data on house or block level [4]. However, high resolution data goes together with challenges in image analysis [5] and traditional statistical analysis of single pixels have been exceeded by state-of-the-art object-oriented concepts [6]. Many ideas concerning image segmentation approaches/tools [7] [8] [9] and object-oriented classification in urban areas [10] [11] [12] [13] have since been presented.

Although [14] presented a worthwhile approach for urban structure detection with building height estimation by high resolution satellite data, a higher level of detail and accuracy can be reached utilizing LiDAR data. Various approaches of building extraction solely from LiDAR data [15] [16] or joint analysis with multispectral image data [17] [18] have been made.

The structuring of a city by means of remote sensing data is very much dependent on the data used [19] and the purpose of the structuring. For urban ecological purposes it has been shown a straight-forward concept of structuring the city into urban biotopes [20] [21]. A similar concept was adapted to the needs of the built-up landscape in terms of urban structural types (UST) [22]. These are spatial units – mostly on block level – that are characterized by their landcover, landuse and the type of urban fabric. In terms of the urban fabric, areas of homogeneous urban morphology are grouped together based on their physical appearance and usage. The parameters on which the buildings are classified are: size, shape, height (floors), density and proportion of impervious surface / vegetation.

Area-wide mapping of UST by means of remote sensing techniques is often done by visual interpretation of Color Infrared (CIR) aerial images or terrestrial investigations [23] – which can be a quite laborious task in large cities. Although this method leads to a high grade of quality, it goes together with the disadvantage of infrequent updating. Modern concepts by image segmentation techniques of CIR aerial photographs [24] or even automatic classification approaches of topographic maps [25] show the potentials and limitations to area-wide mapping.

This paper focuses on the derivation of UST on the basis of a stable and transferable classification approach utilizing both VHR satellite imagery and airborne LiDAR data.

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II. Study areas and Data Sets

Even though every city has evolved its own characteristic shape through individual urban development over time, basic similarities of urban fabric can be found within the same cultural area. For this study, we apply our model to two German cities – Cologne and Dresden (Fig. 1).

A. Cologne

With about 1 million inhabitants, Cologne is today the fourth largest German city (after Berlin, Hamburg and Munich). Its location at the Rhine - in the federal state of North-Rhine-Westphalia - made it an important center for trade and commerce which brought wealth and power to the city. Through various city expansions – especially since the late 19th century – the city has grown and shaped its today's typical concentric footprint. Although large areas of the city were destroyed during World War II, the structures of the city were mostly restored.

B. Dresden

Located at the River Elbe in the east of Germany, Dresden – the capital of the federal state of Saxony - is home to about 500,000 inhabitants today. While the city has played a negligible role throughout most part of its history, it has experienced a tremendous growth during the Industrialization in the 19th century. Its growing economical power and incorporations of surrounding villages has led to a tenfold increase of population to its today's size. As well as Cologne, Dresden suffered severe damages through bombing raids in 1945 which have destroyed large areas – especially around the city center. The establishment of the German Democratic Republic has influenced the reconstruction after the war and the today's shape of the city. Narrow alleys and streets were replaced by large representational avenues meeting the ideas of a socialistic city. The problem of housing shortage in the mid 1970's was faced with large areas of Plattenbauten.

Figure 1. Location of the study sites Cologne and Dresden.

C. Data sets

For the derivation of the UST we utilized a set of VHR optical satellite imagery and a digital surface model derived by airborne laserscanning covering the entire area of both cities (Table I). Since 1999 a new generation of VHR satellites provides Earth Observation (EO) data on a high level of detail. The sensor Ikonos maps the earth's surface with a geometrical resolution of 1m panchromatic and 4m multispectral which meets the needs of interpretations of the highly small-structured urban landscape. Airborne laserscanning (ALS) or LiDAR (Light detection and ranging) is – in contrary to optical satellite sensors – an active remote sensing system. It measures the running time of a laser beam between the sensor, the reflecting surface and back. By means of GPS (Global Positioning System) and INS (Inertial Navigation System) the absolute position of the reflecting object - in x, y and z-direction - can be distinguished [26]. Depending on the density of the laser beams, the geometrical resolution may vary between a few centimeters and a few meters. A very common utilization of the point cloud is the generation of a high resolution DSM (Digital Surface Model).

TABLE I. Characteristics of utilized data sets.

	Characteristics of utilized data sets			
	Cologne		**Dresden**	
	Date	***Resolution***	***Date***	***Resolution***
ALS	2007	1m	2001	1m
IKONOS (no. of scenes)	08/2007 (5)	1m (pan.) 4m (ms.)	05/2007 07/2007 (3)	1m (pan.) 4m (ms.)

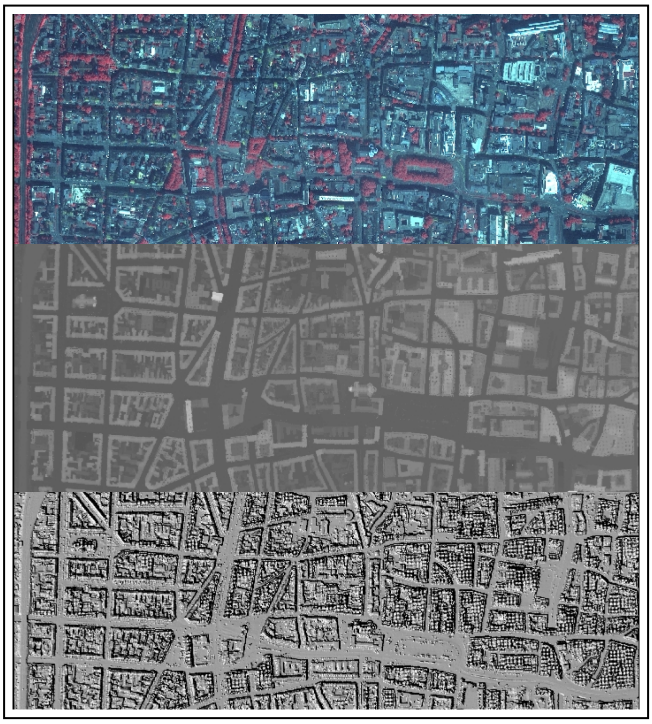

Figure 2. Representation of the same area (Cologne) in different data sets (top: Ikonos false-color composite 4/3/2, middle: DSM, bottom: shaded relief).

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III. METHODOLOGY

One of the major objectives of this study was to develop a transferable rulebase for the application on various study areas on the basis of VHR optical satellite imagery and LiDAR data. Such a kind of joint analysis of two very different data sets brings both advantages and problems with it. On the one hand, the depth of information increases significantly but problems related to different viewing geometry and acquisition dates/times have to be encountered. The different representation of objects in the two data sets is visualized in fig.2. The presented methodology is a fixed modular-based framework which can be interactively adjusted by the user to the data used and the investigated urban environment. In general, the framework is grouped into two major modules, each tailored to the specifications of the characteristics of the two data sets. They may be processed independently from each other, so the user can decide in which order he wants to process the data sets, but if both data is utilized, best results are achieved following the presented workflow. Both modules follow the same workflow: (a) image segmentation and (b) object-oriented classification. With the emergence of the latest generation of satellite images, traditional pixel-wise classification methods have been mostly replaced by object-based methods. Spectral heterogeneity of the images – especially in highly structured urban areas – make it a difficult task to a meaningful classification of the image since single pixels do not represent the important semantic information [28]. Image segmentation algorithms aim at grouping and merging neighboring objects based on their spectral homogeneity or splitting based on heterogeneity respectively [29]. A graphical overview of the presented workflow is shown in fig.3.

A. Module I – DSM

Core piece of the urban structure analysis is the detailed discrimination of building footprints. Even though delineation of buildings based on optical satellite imagery achieves high classification results, improvements towards the derivation of a distinct boundary and the building elevation may be accomplished. In many cases, off-nadir direction angles of the satellite sensor cause a 'tilting' of elevated objects in the scene and impede a proper discrimination of the building footprints. Furthermore, overlap of vegetation (e.g. high trees) may as well reduce the quality of the delineation and result in fuzzy outlines which may complicate the proper description of the shape of a building (fig.4). Both issues play only a minor role in the DSM through the acquisition geometry of the ALS and acquisition time over urban areas; to minimize vegetation effects, acquisition takes place beyond the growth period.

a) Segmentation

Similar to *Module II – VHR-opt*, the segmentation for the DSM is implemented in a fixed, hierarchical workflow and the parameters may be adjusted by the user.

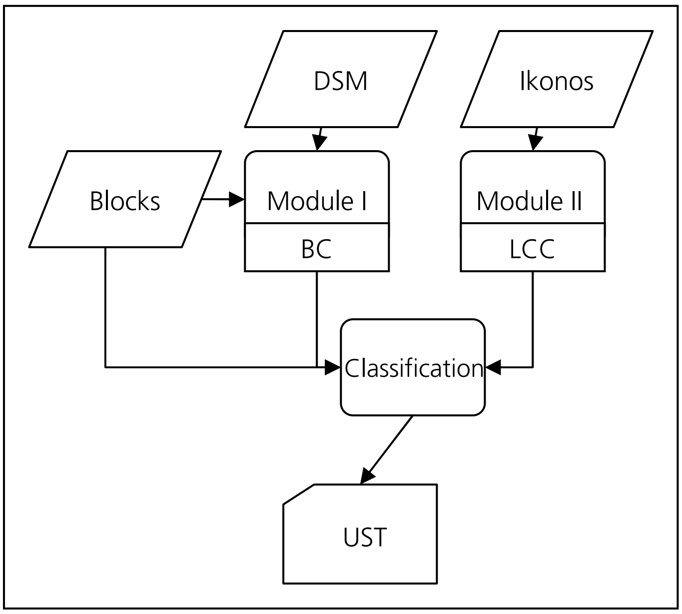

Figure 3. Flowchart of UST-classification.

Before the actual image segmentation is started, the DSM is filtered by a 5x5 median filter to remove artifacts and smooth the boundaries. Then, a basic segmentation level (L1) is created, which represents image objects at the size of one or several building blocks.

This can be done either by multiresolution segmentation with a very high scale factor, or by importing an additional external data layer. An appropriate layer has turned out to be block boundaries provided by ATKIS (Official Topographic Cartographic Information System) which are nationwide available. This data proved to be advantageous as it can be used as initial segmentation level and as classification boundaries in the final step. Based on these spatial units, the algorithm calculates statistical parameters for each image object in L1 like minimum and maximum pixel value, quantiles and mean value of the blocks. Quantiles have proven to be more stable against outliers - which couldn't be removed by the median filtering - so Q10 and Q99 serve as minimum and maximum pixel value, respectively. These parameters are applied with a contrast split segmentation algorithm on every object in L1 to separate bright (elevated) image objects from dark (non-elevated) image objects which are then created in a separate level below (L0). The contrast split is carried out separately for each super-object to gain best fitting, local splitting thresholds. To keep processing time low, only blocks which are classified as 'built-up' or blocks which exceed a threshold between the minimum and the maximum pixel value are selected for further processing. For very large objects in L1, a second contrast split segmentation with updated statistics can be performed to extract additional objects. The application of this method on the two data sets of Cologne and Dresden has shown the significant advantage - in terms of processing time and accuracy - of the hierarchical workflow to a scene-wide approach.

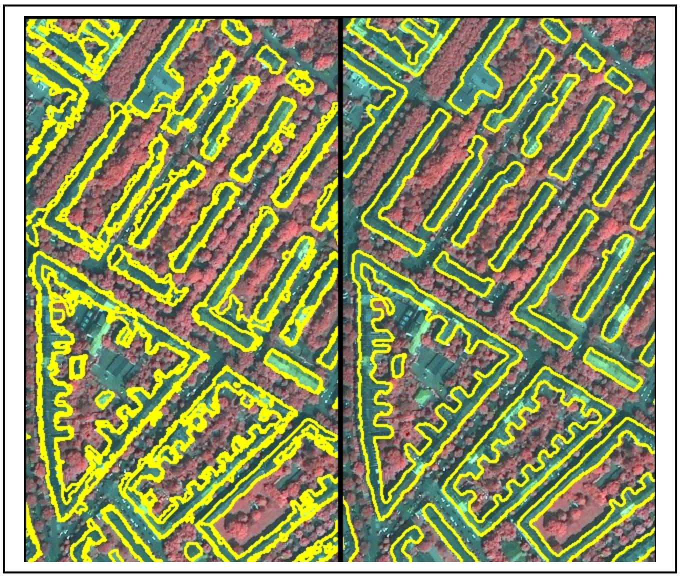

Figure 4. Representation of building outlines derived by Ikonos (left) and DSM (right) (overlaid on Ikonos false-color composites 4/3/2).

b) Object-oriented classification

The first step in classification of the created image objects is to identify which objects actually represent building outlines. A fuzzy-logic classification approach is applied to separate building-objects from non-building objects. Several image object features are then evaluated regarding their relationship with their object-neighbors, the area of the object, and the relationship of its feature values and size to its super-object. The output of this first classification process is a 'building mask' showing the boundaries of the building polygons (fig.4).

In the second step, the buildings are further classified based on their shape criteria. The building size can be described by its area and its elevation. Whereas the area for each image object is simply calculated by the number of pixels multiplied by the pixel size, the elevation of each building object has to be retrieved by calculating the difference of its mean absolute height to the mean absolute height of its next surrounding ground. For generalization reasons due to easier interpretation, the elevation of each building is expressed in floors. The number of floors for each object is estimated by dividing the elevation of the building by a constant – a mean value for a sample of visually inspected objects with reference data (field surveys and visual inspection of aerial imagery). A further criterion for the building classification (BC) is the shape of the buildings. For this purpose, a fuzzy logic classification – utilizing more than 20 features - is applied and classifies the buildings in – so far – five different building classes: 'non-residential/industrial', 'detached/semi-detached', 'terraced', 'building blocks' and 'high-rise buildings' (fig.5). On the basis of these built-up areas the building density is calculated on block level for further differentiation of the UST.

B. Module II – VHR-opt

The methodology of the workflow for VHR-opt (optical) satellite imagery on various sensors (Ikonos and Quickbird) was presented by [10] [13] [27] and proved to be a stable and transferable methodology for the derivation of various landcover classes in various urban areas.

a) Segmentation

The hierarchical image segmentation optimization procedure aims at extracting real world segments in one single level. At first, a basic segmentation level (L-1) is created with a very low scale parameter which splits the image into rather small objects. This step is iteratively followed by optimization steps where image objects with a spectral similarity are merged together on the next segmentation level (L0) with an increased scale parameter. The same procedure is repeated until objects in the final segmentation level (L1) represent both small objects in highly structured areas (e.g. roofs, cars) and large combined objects with a high homogeneity (e.g. meadows). If this step is processed after Module I - DSM, the objects representing the building outlines are imported and kept throughout the segmentation and classification process.

b) Object-oriented classification

The final step of the first module is a multi-level fuzzy logic [30] based classification approach. The image objects are assigned to a class based on its individual membership value to the corresponding class. The classification process is a hierarchical process where objects in the optimized segmentation level (L1) are classified first until the final classification is reached on the basic segmentation level. To ensure a stable transferability, the membership functions of each class are based on the shape characteristics of the image objects, assuming that e.g. streets are represented similarly in various urban areas.

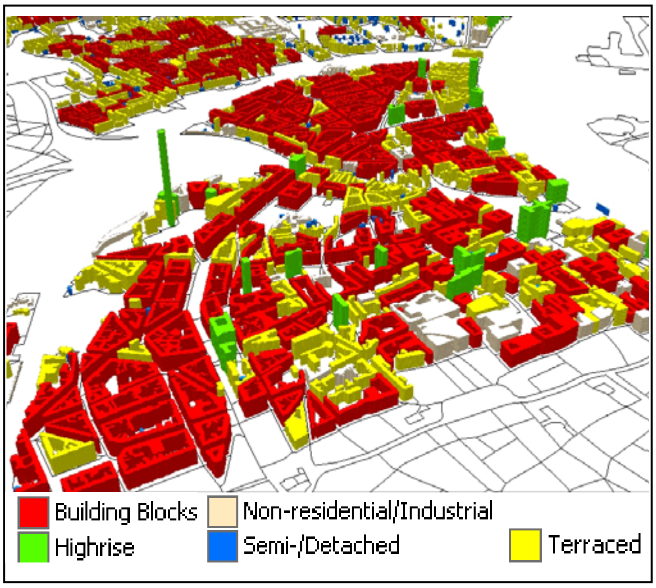

Figure 5. Perspective-view of classified buildings in Cologne overlaid on the building blocks with building elevation in proportion to their number of floors.

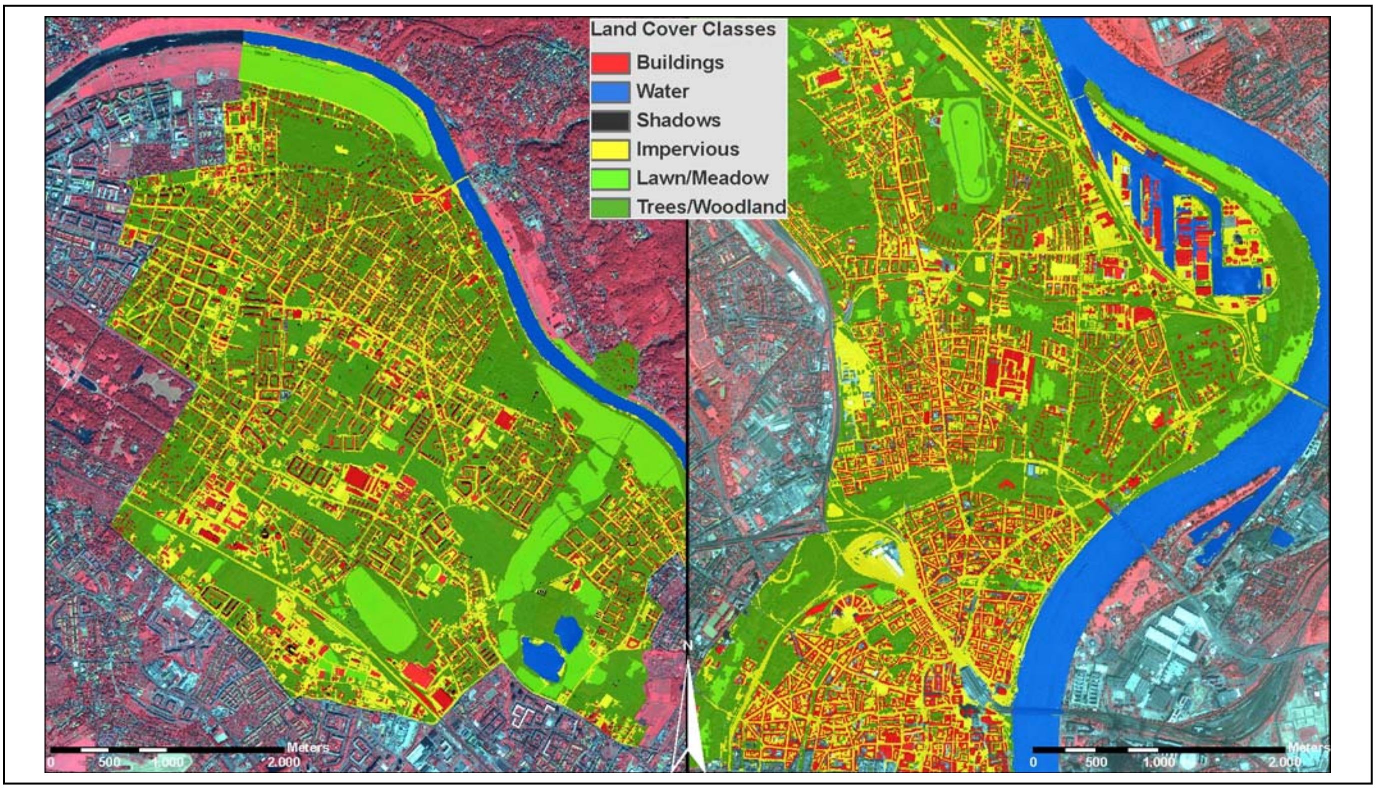

Figure 6. Results of landcover classification for the study areas in Cologne (left) and Dresden (right) (overlaid on Ikonos false-color composites 4/3/2).

The NDVI (normalized differenced vegetation index) is the only spectral information utilized for the classification process. The results of the landcover classifications of Module II – VHR-opt are shown in fig.6.

C. Classification of UST

The added-value of this joint analysis is fully utilized when the information of both data sets – high-resolution landcover classification and morphological information on buildings – contributes to the classification of urban structural types. As well as mere optical data lack detailed parameters for in-depth characterization of buildings, UST cannot be classified properly solely on the basis of buildings due to missing landcover information. In the last step of the classification process, all information derived from the data sets by Module I and Module II is utilized to classify the distinct UST. As mentioned above, UST are marked-off spatial units characterized by mostly homogeneous landcover and landuse. For the final classification of the urban structural types, three hierarchically arranged object-levels are utilized: the basic level is represented by the landcover classification, the second level holds the information for the buildings and the highest level is represented by the same block boundaries which served as basic segmentation level. In a first step, large water surfaces and large vegetated areas are extracted from the landcover classification into the highest level. Furthermore, blocks with a high percentage of vegetation cover and a very low building density are assigned to the distinct UST-class. Blocks holding information about classified buildings and building density in their sub-object-level are assigned to a class represented by the most frequent building type. When two building types are represented equally, the class is a mixed class of both. This extends the five basic building types to 16 built-up UST including a ‘mixed-type’ which is assigned when a block holds more than two different building types or when the buildings could not be classified to one of the basic building types. Together with four non-built-up classes (‘lawn/meadow’, ‘trees/woodland’, ‘water’ and ‘open space’) a total number of 20 different urban structural types is classified.

IV. RESULTS AND DISCUSSION

As mentioned above, the classification of UST in Germany is mostly based on visual interpretation of remotely sensed imagery and therefore prone to subjective interpretation by the operator. Additionally, a Germany-wide classification key – not to mention an entire classification – is missing. Therefore, the validation of the results has been carried out in three steps: accuracy assessment of buildings, the landcover classification and the UST.

Table II lists the overall accuracy of detected buildings for the study areas: in Cologne, 88.5% of the buildings greater than or equal one floor from the reference data set (official digital building model Cologne, 2007) have been detected, and 98% for buildings greater than or equal two floors, respectively. The accuracies for the study area in Dresden show 81.2% detected buildings greater than or equal one floor and 102.6% greater than or equal two floors.

TABLE II. ACCURACY ASSESSMENT OF BUILDING DETECTION (DATE OF DATA ACQUISITION IN BRACKETS).

Accuracy assessment of building detection				
	Cologne		Dresden	
Nr. of buildings	*Reference (2007)*	*Classification (2007)*	*Reference (2008)*	*Classification (2001)*
≥ 1 floors	2730	2417	4490	3648
≥ 2 floors	2362	2316	3436	3524

TABLE III. ACCURACY ASSESSMENT OF FLOOR ESTIMATION.

	Accuracy of floor estimation %				
	Deviation of floors				
Cologne	*≤ -2*	*-1*	*0*	*+1*	*≥ +2*
2 floors	-	1.49	78.77	18.25	1.49
3 floors	-	24.36	63.61	10.60	1.43
4 floors	2.51	38.19	49.75	8.04	1.51
5 floors	14.58	60.42	18.75	2.08	4.17
≥ 6 floors	54.55	32.47	7.79	2.60	2.60
mean	14.33	31.38	43.79	8.31	2.24
		83.43			
	Deviation of floors				
Dresden	*≤ -2*	*-1*	*0*	*+1*	*≥ +2*
2 floors	-	-	72.37	26.65	0.98
3 floors	-	16.90	71.83	10.62	0.65
4 floors	2.21	35.29	59.56	2.70	0.25
5 floors	12.50	77.27	9.09	1.14	-
≥ 6 floors	26.42	66.04	7.55	-	-
mean	8.22	39.10	44.08	8.22	0.38
		91.40			

Reasons for this may be found in the temporal difference of the reference data set (official digital building model, Dresden, 2008) and the acquisition of the ALS-data. The elevation of the buildings is very crucial information for the determination of UST. Floors are derived by the mean elevation of each building divided by a mean floor-height, which was estimated as 3.35m. The overall accuracy of floor estimation show that 83.43% (Cologne) and 91.40% (Dresden) respectively, of the buildings have been estimated with a maximum deviation of one floor (Table III).

TABLE IV. ACCURACY ASSESSMENT OF LANDCOVER CLASSIFICATION.

Accuracy assessment of landcover classification				
	Cologne		Dresden	
LC class	*User accuracy %*	*Producer accuracy %*	*User accuracy %*	*Producer accuracy %*
Buildings	95.00	87.16	95.00	79.83
Impervious Surface	87.00	82.08	83.00	85.57
Lawn / Meadow	87.00	89.69	89.00	80.91
Shadow	96.00	100.00	94.00	98.95
Tree / Woodland	80.00	82.47	71.00	89.87
Water surface	95.00	100.00	100.00	100.00
Overall accuracy %	**90.12**		**88.93**	

While for the majority of buildings lower than or equal four floors, the number of floors is classified correctly, a clear underestimation of floors for buildings higher than or equal five floors is observed. Visual inspection of underestimated buildings at four and five floors, show a high percentage of old buildings with higher average floor heights than recent developments. However, higher accuracies may be achieved with adjusted mean-floor heights for various kinds of buildings.

Accuracy assessment of the landcover classifications was carried out by visual validation on the basis of 100 randomized reference points for each class. The results are shown in Table IV. Generally, the classification accuracy strongly benefits by the joint analysis of the DSM and VHR-satellite imagery and shows the potential of the integration of elevation and optical data.

The final classification of the urban structural types for both study areas in Cologne and Dresden are presented in fig. 7. In Cologne, 704 objects are represented as built-up after the final classification process. While 68.2% of the built-up blocks are assigned to one of the five basic building types, 18.7% are classified as one of the 15 built-up classes which contain two building types. 13.1% of the blocks could not be assigned to a specific built-up class due to either more than two building types within the same block or because the building cannot be represented by one of the classes or by misclassification and is therefore classified as ‘mixed’. For the study area in Dresden, a total number of 739 built-up blocks was classified of which 41.5% have been assigned to one of the five basic built-up classes. While only 7.2% show an equal representation of two different built-up types, the majority (51.3%) of the built-up blocks was assigned to the class ‘mixed’ without further distinction of the comprised building types. Reasons for this are specific, but also frequent building types which could not be assigned to any of the five classes as well as a higher degree of heterogeneity within the blocks.

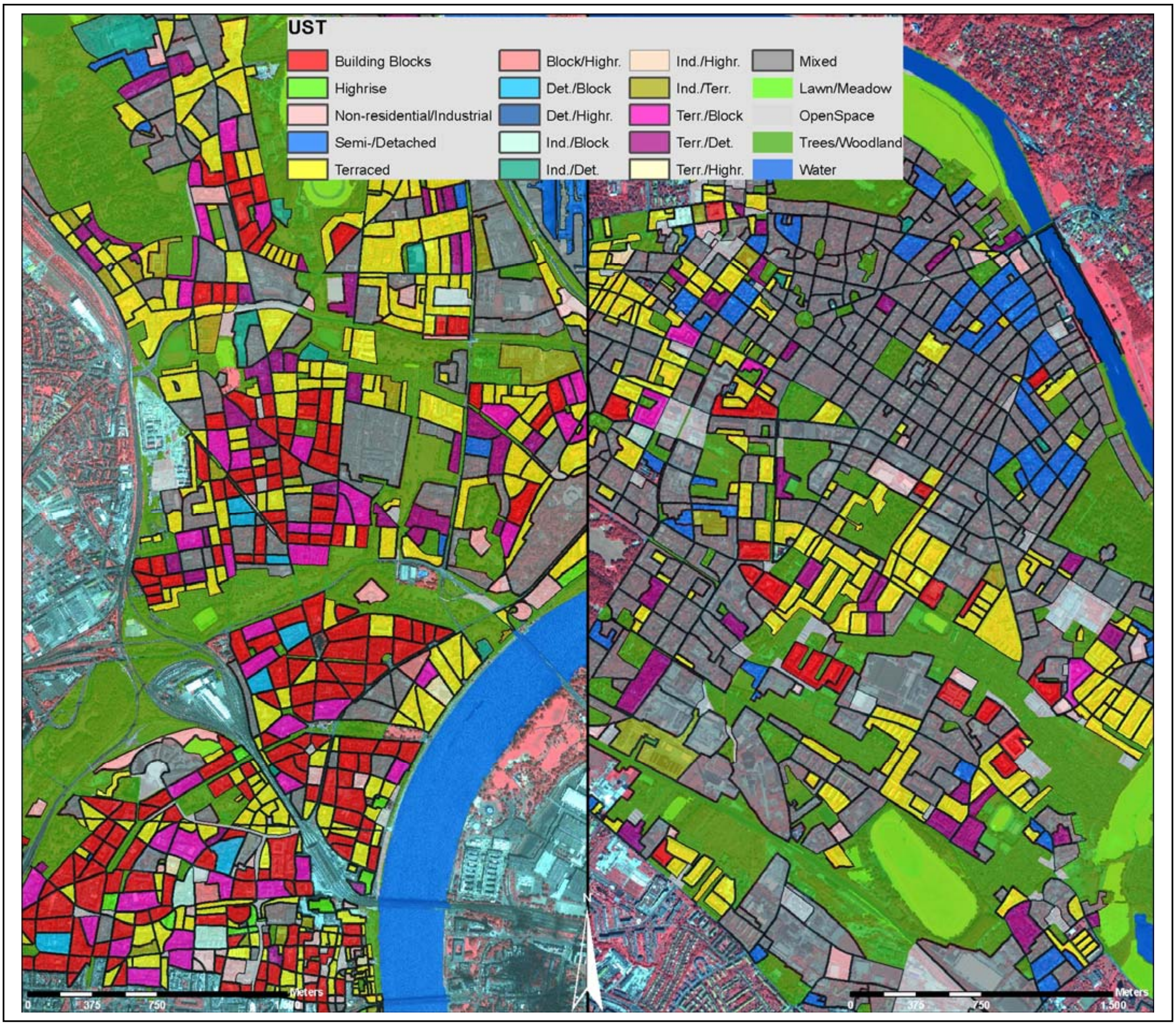

Figure 7. Result of classification of UST for the study areas of Cologne (left) and Dresden (right) (overlaid on Ikonos false-color composites 4/3/2).

V. Conclusion and Outlook

In this paper we presented a straightforward, multisensoral approach for urban structuring in terms of urban structural types for two cities in Germany with different historical development and different urban fabric. A modular concept for urban structuring with both high-resolution optical satellite imagery and a DSM derived by airborne laserscanning, has been implemented. Both modules are autonomously accessible and can be run independently from each other. In this way, a stepwise classification of UST – or solely landcover or building morphology – can be obtained. The developed methodology has focused on a stable and transferable extraction of the features for area-wide application on two different study areas and showed an accurate classification of buildings, their elevation and landcover information. This information is utilized for the characterization of homogeneous blocks for the classification of UST and the results show the potential of this joint analysis. Future research will focus on the development of a nation-wide, further subdivided classification key for UST and the application on additional study areas for comparison of the urban morphology between various cities. Harmonisation of the classification of urban structural types in various cities also aims at future analysis of the integration of remote sensing and socioeconomic parameters, e.g. if similar urban morphology show similar socioeconomic parameters of the population residing there.

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