Automatic Derivation of Urban Structure Types from Topographic Maps by Means of Image Analysis and Machine Learning

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Abstract. This paper presents a method for automatic derivation of urban structures types with focus on residential areas. It is based on scanned topographic maps at scale 1:25k and a given urban block geometry from a national topographic database. The procedure consists of five steps: (1) definition of a typology of urban structures, (2) extraction of building footprints, (3) computation of measurements to describe the urban structure (4) building classification and (5) derivation of urban structure types on block level.

Keywords: Topographic Maps, Urban Structure, Machine Learning

1. Introduction

Urban geography and urban planning require detailed information about the functional, morphological and socio-economic structure of the built environment. The building stock is the most important component in settlement areas. It directly affects urban structure, e.g. urban form, density of housing and distribution of population. Studying the built environment as an interdisciplinary research object requires a common spatial working basis. One approach is to set up urban cover types (Pauleit and Duhme, 2000), also known as *Urban Structure Types* (UST). It is a domain-independent concept that describes spatially homogeneous regions in terms of the land cover (water, meadows, settlement etc.), land use (residential, non-residential etc.) and other physical characteristics (building size, density, arrangement etc.). Urban structure types on mid-scale level (e.g. statistical block level) can thus be used for interdisciplinary studies, e.g.

modeling quality of housing, material flows and energy consumption or other socio-economic and ecological aspects.

Despite of the great importance of analyzing urban structure for science, planning and politics, there is no nation-wide data base on block level. Mapping USTs is still mostly based on visual interpretation of aerial photographs and maps and is a very time consuming process. Automatic approaches based on remote sensing data can offer an efficient alternative. However, such approaches have been tested on selected cities only. They also presuppose the availability of radiometrically homogeneous images which are very expensive. Topographic maps at scale 1:25,000 are a low-cost alternative. They are nationwide available and comprise of very homogeneous data. Their temporal coverage reaches back to the very beginnings of large-scale topographic mapping. Therefore they allow studies on dynamics and developments of settlements over much longer periods then satellite imagery.

2. Related Work

To explain causes and results of dynamic processes in rapidly growing metropolises has driven science to develop effective methods to capture land cover and land use structures as well as their change. With the satellite remote sensing technique, developed at first for the military reconnaissance purposes, it got possible to look at the earth's surface from above and to map larger areas of interest. The recording of the natural resources was a main aim in the beginnings of the civilian use of these new data. Aerial and satellite imagery and the human ability of visual perception allow us to recognize and map urban land cover and land use types in an efficient way. Within the 1970s years the United States Geological Survey (USGS) developed a standardized scheme for the interpretation of data on different levels (Anderson et al., 1976).

First attempts at the automatic derivation of land use classes from remote sensing data were kernel based methods (e.g. Wharton, 1982; Barnsley & Barr, 1996; Gong & Howarth, 1992). Based on a classified image the spatial context of every pixel has been analyzed in terms of composition and the spatial arrangement. Barr and Barnsley made an important contribution to the transition of the land cover to the land use on the basis of a graph based structural attempt (Barnsley & Barr, 1997; Barr & Barnsley, 1997). Their approach sets up on discrete land cover regions, which can be achieved with image segmentation techniques from remote sensing data. Further a structural description of the regions with regard to morphological qualities (e.g. area, compactness) and their spatial relations (e.g. adjacency,

inclusion) is carried out. The authors showed that it is possible to distinguish urban land use classes on the basis of morphological qualities and neighborhood relations derived in the graph (Barnsley & Barr, 1997, Barr et al., 2004). Such studies (see also Herold et al., 2003; Mesev, 2005) provide an important contribution to the empirical support of the thesis of the relation between the urban form and the function (Batty & Longley, 1994). This graph-based approach has been recently used by Walde et al. (2013), too.

During the last few years, some work has been done concerning the automatic identification and classification of urban structure types. Many of the early approaches use remote sensing imagery, whereas topographic vector data and LiDAR data take on greater significance more recently. Important studies in this context are in a chronological order Herold, Liu and Clarke (2003), Bauer and Steinnocher (2006), Wu, Xu and Wang (2006), Dogruso and Aksoy (2007), Banzhaf and Hofer (2008), Meinel et al. (2008a, 2009), Wurm et al. (2009), Bochow (2010), Vanderhaegen and Canters (2010), Colaninno, Cladera and Pfeffer (2011) and Walde et al. (2012).

3. Urban Structure Types

A typology of urban structures can be constructed under consideration of a typology of urban structures can be constructed under consideration of different criteria. According to the classification scheme of Meinel et al. (2008), 10 urban structure types can be distinguished (Fig. 1). On the first level residential and non-residential buildings are differentiated. Residential buildings can be further subdivided into single/two family houses and multi-family houses. On the next level the single/two family houses can be detached/semidetached (SFH-D), terraced (SFH-T) or rural houses (SFH-R). The multi-family houses in turn are classified into open (MFH-O) or closed (MFH-C) with respect to the arrangement of buildings in a block. Moreover there are traditional row houses (MFH-TR), industrial row houses (MFH-IR) and high rise buildings (MFH-HR) having height greater than 22m (MFH-HR). Non-residential areas are industrial or commercial (IC) and buildings of special purpose (SP).

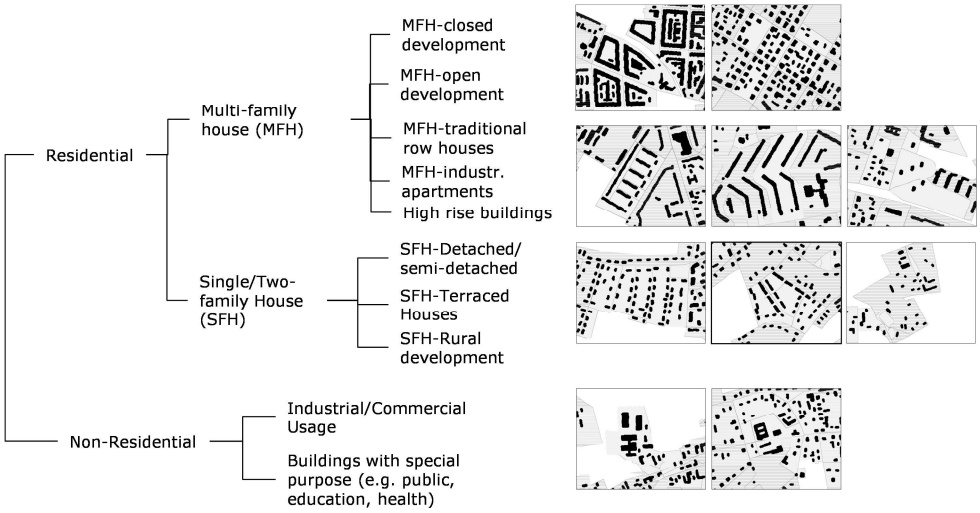


Figure 1. Building Typology after Meinel et al. (2009)

4. Data sources to describe urban structure

In Germany, there is no official data source that contains detailed information on urban structure types. Existing digital landscape models only differentiate between a few land use classes such as residential, commercial, and industrial. For many applications, this thematic resolution is simply too low. Local surveying offices sometimes conduct local urban structure mappings. However, these mappings are costly and the obtained data are heterogeneous due to different classification criteria.

For the visual classification of urban structure types various data can be used, such as remote sensing imagery (air- and spaceborne), topographic maps and plans, and the verification at the site (“ground truthing”). Previous approaches to automatic mapping of the urban structure mostly use remote sensing data, also known as "urban remote sensing". It is used to describe land cover and land use in high spatial and thematic resolution to answer scientific questions from the areas of the settlement and town geography, urban research, urban morphology, and planning.

Table 1. Possible data sources for the acquisition of urban structure types.

	Remote sensing imagery			Topographic base data	
	Satellite imagery	Aerial photography	LiDAR data	Cadastral data, digital landscape models	Topogr. Maps
Spatial coverage	yes	yes	partly	yes	yes
Temporal coverage (last 5 decades)	partly	yes	no	no	yes
Automatic building extraction	possible	partly	possible	possible	possible
Continuation	assured	assured	uncertain	assured	assured
Data costs	moderate	high	high	high	low
Horizontal homogeneity	good	poor	moderate	good	good
Vertical coverage	poor	poor	moderate	good	good

Table 1 gives an overview of various data sources and their characteristics. One disadvantage of satellite data are their availability only for the last decades, while topographic paper maps and plans exist also for “pre-digital” times. In the following work, the focus is therefore set to the automated derivation of urban structure types from topographic maps.

5. Workflow

The approach for an automatic derivation of urban structure types consists of several steps, which will be described in the following subsections. Figure 2 shows the proposed and applied workflow.

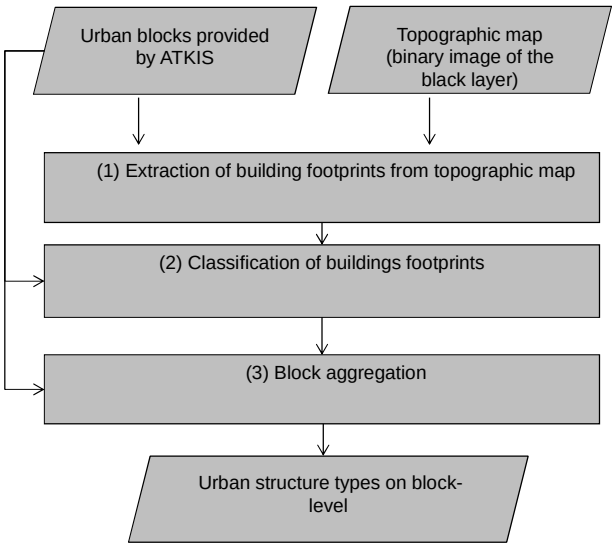


Figure 2. Applied workflow for the derivation of urban structure types.

In order to make use of the building footprints depicted in scanned topographic maps, methods of cartographic pattern recognition and image analysis have to be applied. In the first step the building footprints are extracted from the binary map image (1).

The second step is the classification of building footprints according to a given typology (2). This process of classification includes feature extraction, feature selection, classifier design, model selection and accuracy assessment. During the development of a classifier different machine learning classifiers such as Support Vector Machines (SVM) and Random Forest (RF) will be tested and compared to each other to choose the best. SVM has already proved to be applicable in land cover classification (Foody & Mathur, 2004; Brenning et al., 2006) and building classification (Steiniger et al. 2008). Other algorithms like Bagging and Random Forest have not yet been used for building classification.

In the third step, the classified building types are aggregated to USTs by means of the dominating building type within the urban block. Based on a given visual UST mapping of the City of Dresden, Germany, an accuracy assessment has been carried out.

5.1. Input Data

The German topographic map at scale 1:25K is a nationwide and multi-temporal available low-cost data source for building footprints. In advantage over larger scale maps such as 1:5K and 1:10K, it provides nationwide mostly homogenous representations of the building footprints. However, the buildings are presented in the same black map layer as transportation and vegetation signatures.

In addition, urban blocks are used, which are provided by a national topographic database called ATKIS® base DLM. On one hand, the geometry provides important information during the feature extraction process. On the other hand, it serves as an aggregation unit to derive the USTs. The use of this database also offers additional information about the land use. Non-residential buildings (industrial/commercial buildings and buildings with special purpose) can be easily separated from residential buildings. Since the focus is on residential structures, a classifier needs to be trained to separate the 8 residential building types only.

5.2. Cartographic pattern recognition for building footprints

The above described characteristics of map images require methods of cartographic pattern recognition to make the contained information explicitly available for spatial analysis and classification. For the exclusion of linear map objects, morphological filters are used. After a connected-component analysis all candidate objects are classified into a set of building and non-building objects following the methodology described in Herold et al. (2012). The detection rate for map symbols and signatures is in average 96%, depending on the map quality and digitalization parameters. The building footprint loss due to overlapping map symbols and generalization is less than 1%.

Figure 3. Building footprint retrieval from a topographic map.

5.3. Features for automatic building classification

For the classification different measurements (features) are derived by means of image processing techniques and spatial analysis. In contrast to remote sensing imagery, topographic maps contain discrete map objects and no spectral information. Therefore, only geometric, topological or contextual features and relations can be used.

Table 2 shows a selection of the defined measurements. The measurements have been derived using HALCON (commercial software for machine vision, www.mvtec.com/halcon). For a detailed description of the features see Meinel et al. (2008) and Hecht (2013).

Name	Notes
AreaH	Area of the building object [m²]
Peri	Perimeter of the building object [m]
AreaRect	Area of the minimum bounding rectangle [m²]
Convex	Measurement to describe the convexity, proportion of AreaH and the area of the convex hull
Circular	Measurement to describe the circularity (compactness) of a building
PixDist	Mean distance between the centroid and building contour points [m]
MaxDiam	Maximal distance between two building contour points [m]
RectLeng	Length of the minimum bounding rectangle [m]
RectWid	Width of the minimum bounding rectangle [m]
HR	Binary variable is true, if a special signature for high rise buildings was detected [0/1]
NuBuildBl	Number of buildings in a urban block
NuBuildBu	Number of buildings in a 100 m buffer
AreaBlock	Area of the urban block [m²]
NBPBA	Building density in a urban block [1/m²]
BLARERAT	Building coverage rate in a urban block [%]
MinBlDist	Minimal distance of the building contour to the urban block boundary [m]
...	...

Table 2. Selection of various morphological building features.

5.4. Classifier Design

In previous works structure types have been derived through an automatic building classification based on a knowledge-based rule set (Meinel et al. 2009). Due to the high variability of data quality such a rigid classifier may fail in applying it to different maps. Pattern Recognition and Machine Learning provide a wide spectrum of learning algorithms to analyze data and recognize patterns, used for object classification (e.g. Duda et al., 2000). Since a user-specific building typology is given, a supervised learning strategy has been preferred. The training is carried out on building level, which makes the availability of sufficient training data needed.

In a model selection process different machine learning classifiers has been tested and compared to each other. For evaluation a 10-fold cross validation has been applied, since this is a standard approach to estimate the generalization error. After choosing the best classifier, all buildings of the City of Dresden, Germany, are classified. Afterwards the USTs are derived on urban block level through an aggregation procedure. Finally, based on a given UST mapping of the City of Dresden, an accuracy assessment has been carried out.

5.5. Tested classifiers

During the development of a suitable classifier, different machine learning techniques have been tested (Table 3). These are *Support Vector Machine* (SVM) with a Gaussian radial basis function as a kernel as well as ensemble based classifiers, like *Bagging Trees* (BAGGING) and *Random Forest* (RF). In addition classic learning algorithm such as the *k-nearest neighbor classifier* (KNN) and *Classification and Regression Trees* (CART) have been tested for benchmarking. Table 3 briefly summarizes the tested methods and its principle.

Abbreviation	Algorithm	Principle
KNN	K-nearest neighbor classifier	Assign the class label most frequently represented among the k nearest samples in the trainings data.
CART	Classification and Regression Tree (Breiman et al., 1984)	Learning algorithm to recursively split the feature space into subsets based on binary decisions. The result is a decision tree, where leaves represent class labels and branches the decisions that lead to those class labels.
BAGGING	Bagging Trees (Breiman et al., 1996)	The CART-algorithm is applied on multiple bootstrap samples. For classification the results of the decision trees are combined by voting.
RF	Random Forest algorithm (Breiman, 2001)	A Random Forest is an ensemble of decision trees, which are constructed based on random samples and a random subset of features. For classification the results of the single trees are combined by voting.
SVM	Support Vector Machine (Vapnik, 2000)	A SVM is based on nonlinear transformations of the features into a higher-dimensional feature space, where the classification problem becomes linear separable. SVM models are basically binary classifiers. With aggregation techniques, these can be made applicable to multi-class problems.

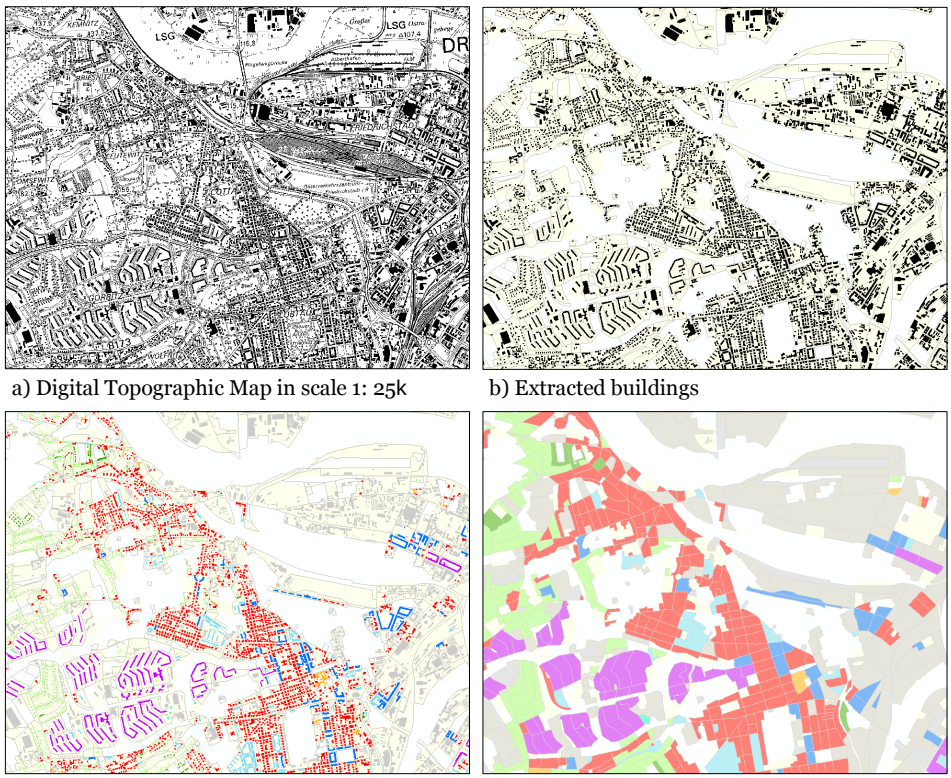
Table 3. Tested classification methods

All algorithms are implemented in packages for R, which is an open-source tool for statistical computing (http://cran.r-project.org).

5.6. Aggregation

After choosing the best method for building classification, the whole building stock has been classified with a model trained with all available training data. Afterwards the defined urban structure types are derived on block level. The structure type is determined by the dominant building type within each block, which is a common criterion in visual aerial photograph interpretation. Thus, for every block exactly one structure type is assigned and a consideration of mixed building types was initially renounced.

Figure 2 shows the principle of automated derivation of the structure type on block level.



a) Digital Topographic Map in scale 1: 25k

b) Extracted buildings

c) Classified buildings

d) Urban structure types on block level

Figure 4. From a topographic map to a thematic urban structure type map.

6. Results

The developed approach has been applied to real geospatial data. As an area under investigation the city of Dresden, Germany, was chosen. As input data, both from year 2006, the digital topographic map DTK25-V and the German digital landscape model (ATKIS® base DLM) have been used. For training and validation 14,810 buildings each with one of the 8 corresponding residential building type according to the predefined classes have been captured.

For evaluation of the derived urban structure type an independent UST-mapping of the City of Dresden has been provided by the City. In a preprocessing, the reference data had to be semantically generalized according to the defined structure types in Fig. 1 (8 residential and 2 non-residential).

6.1. Model Selection

The aim of the model selection is to find the algorithm best suitable for the classification problem. Therefore, the generalization ability of the classifiers was examined and the model with the best performance has been chosen. To measure the generalization ability a 10-fold cross-validation has been applied. To save computing time during the model selection, a subset of 5,000 buildings have been randomly selected for the evaluation. This was necessary since the tuning of the parameters, particularly of the SVM, is a very time-consuming process.

Figure 5 summarizes the accuracy for different classifiers. The highest classification accuracy could be obtained using a Random Forest (74.3 % ±2.3). Applying the CART-algorithm (64.8 % ±2.2) or KNN (68.0 % ±2.0) results in a lower accuracy. The performance of BAGGING (72.5 % ±2.1) and SVM (70.8 % ± 2.1) was moderate.

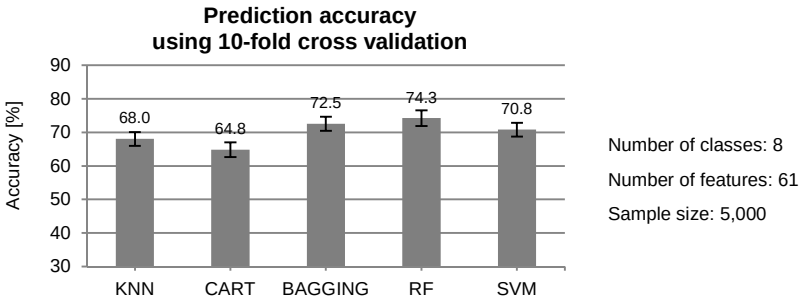


Figure 5. Cross-validated prediction accuracy for building classes.

6.2. Accuracy Assessment on building level

After Random Forest has been chosen as the best classification method for building classification, a detailed accuracy assessment is carried out now based on all available data (n=14,810). For the evaluation the confusion matrix has been computed (cf. Fig. 6).

Prediction \ Reference	MFH-C	MFH-O	MFH-TR	MFH-IR	MFH-HR	SFH-D	SFH-T	SFH-R	Sum	User´s Accuracy [%]
MFH-C	**166**	31	25	13	0	1	0	6	242	69,5
MFH-O	71	**4867**	151	32	8	665	97	163	6054	82,0
MFH-TR	36	109	**884**	112	1	15	68	5	1230	71,9
MFH-IR	9	9	63	**377**	1	1	8	0	468	80,6
MFH-HR	0	0	0	0	**33**	0	0	0	33	100,0
SFH-D	1	767	26	3	2	**4904**	170	93	5966	82,8
SFH-T	0	10	9	3	0	15	**235**	3	275	86,1
SFH-R	3	37	4	0	0	41	1	**456**	542	84,4
Sum	286	5830	1162	540	45	5642	579	726	14810	
Producer´s Accuracy [%]	58,0	83,5	76,1	69,8	73,3	86,9	40,6	62,8		

Ø Overall Accuracy: 80,5 %

SD Overall Accuracy: 0,6 %

Figure 6. Sum of confusion matrices from 10-fold cross validation.

Though using all available reference data for the 10-cross validation an overall accuracy of 80.5 % (±0.6 %) could be reached. The Producer´s Accuracy for terraced houses (SFM-R) and rural houses (SFH-R) is quite low. The confusion matrix shows issues separating detached multi-family houses from single family houses and rural houses.

6.3. Accuracy assessment on block level

After aggregation of the information on block level, the results have been evaluated with an external UST mapping provided by the City of Dresden.

Comparing the results with the reference UST mapping an overall accuracy of 82.3 % could be observed. Terraced house, rural house structures cannot be distinguished adequately. For modeling it is recommended to aggregate these classes to one. High rise building structures have been misclassified due to the dominance rule during the aggregation procedure.

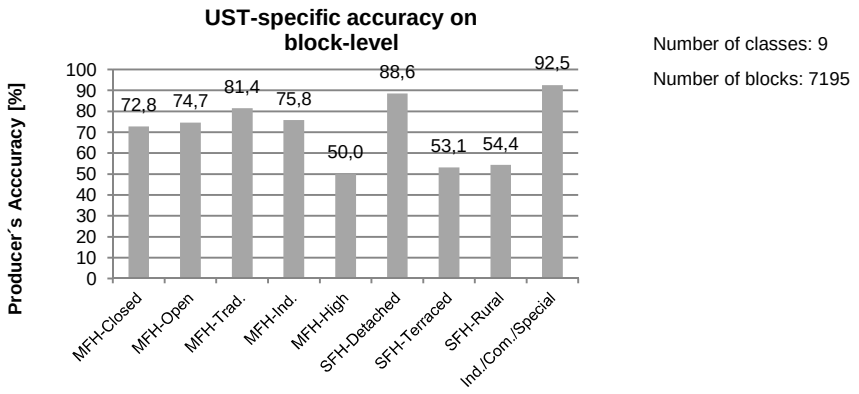
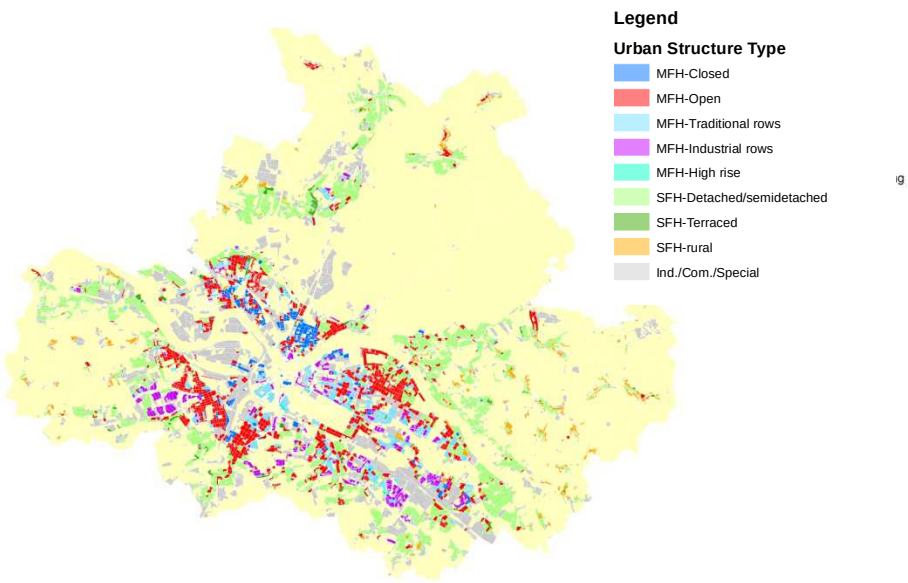
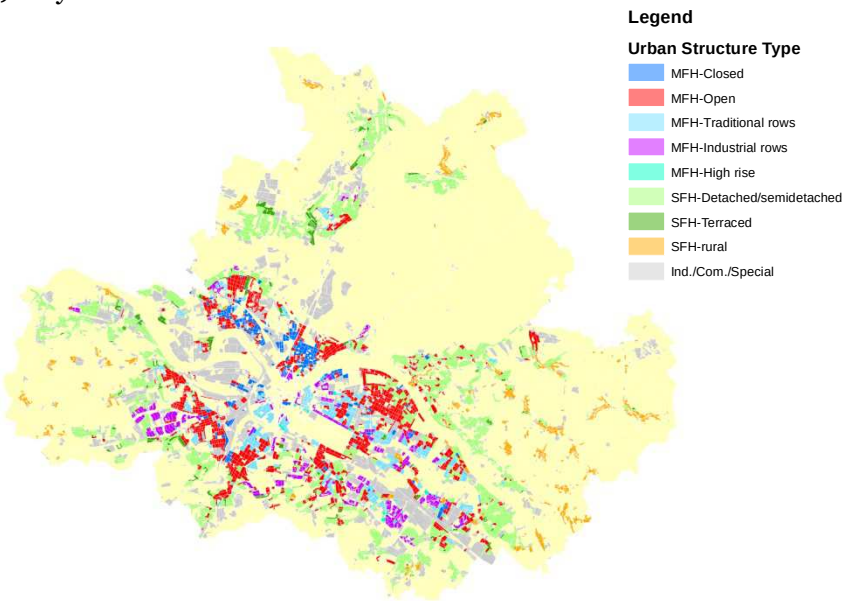


Figure 6. Result of the comparison to reference-UST from Dresden (n=7195).



a) City of Dresden: Reference data



b) City of Dresden: Automatic derived urban structure types

Figure 6. Result of the comparison of the automatic derived UST to a reference mapping from Dresden (n=7,195).

7. Conclusion

Our approach offers an efficient and low cost way to map residential urban structures. Additionally, topographic maps provide the basis for multi-temporal mapping. Therefore, the presented method could be of particular interest for spatial sciences (e.g. studying urban form and dynamics) as well as planning (e.g. infrastructure planning, urban and regional planning).

The comparison of the derived urban structure types with existing mappings has shown an accuracy of over 80%. Although the accuracy suffices the requirements for land use and land cover mapping (Anderson et al. 1976), the producer's accuracy for terraced houses, high rise buildings and rural buildings are unsatisfactory. Thus this approach is only suitable for supra-regional applications, with no other data options.

In the future, further evaluations are necessary. Particularly the method needs to be applied to other test areas in order to examine the transferability.

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