Analysis of 2D/3D Urban Density Indices in Context of Land Surface Temperature

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1 ABSTRACT

Cities worldwide cover only 2 % of earth`s surface but spend almost 75 % of the world`s energy resources (Gago et al. 2013). The emission of heat and the structure of built-up areas can increase the phenomenon of urban heat islands (UHI), which highly infects the well-being of all inhabitants. Future work will focus on monitoring capabilities to manage the development of urban settlements. The study investigates the relationship between urban density indices and land surface temperature (LST) using multi-sensor remote sensing data. All processing steps are performed for the City of Cologne, Germany. The input data are consisting of high resolution multi-spectral Ikonos imagery, as well as an object height model, derived from Light Detection And Ranging (LiDAR) data and thermal information, provided by the Landsat 7 satellite mission. The first working step, the derivation of six land cover (LC) classes, is based on a geographic object based image analysis (GEOBIA) approach. Therefore, LiDAR and pan-sharped Ikonos data with a spatial resolution of one meter are used. In a second step, and based on the extracted LC and object height information, existing and new measures of urban density are computed, that take into account the horizontal and/or vertical characteristics of a city. All measures are separated into single object related and area related indices, depending on the basis of calculation. The significance of different Areas of Interests (AOI) are analyzed and compared for area related indices. Finally, the correlation between multi-temporal LST data, derived from Landsat Enhanced Thematic Mapper (ETM+), and each indicator is calculated with regard to their dependency on the predominant type of urban land use (LU) and the acquisition date (season) of the Landsat ETM+ data.

2 INTRODUCTION

Urban structure and land cover affect the city climate and thus the well-being of their inhabitants (Jusuf et al. 2007:232). Furthermore, certain land cover and building types reduce or intensify temperature (Franck et al. 2013:170, Jusuf et al. 2007:232). Especially buildings with closed forms e.g. block development, high number of floors and narrow roads, interfere the exchange of warm and polluted air with fresh air (Franck et al. 2013:175, Gago et al. 2013:755). Planted areas and tree populations have an opposite effect and cool down their environment because of plant transpiration (Gago et al. 2013:751).

In terms of increasing urban populations, social and ecological factors become more and more relevant for future urban development. The technique of remote sensing can be an efficient tool to characterize and quantitatively describe parameters, concerning urban structure and environmental factors. Several studies deal with the derivation of urban density indices and land use classifications, particularly with regard to high resolution optical datasets (Yu et al. (2010), Tompalski & Wezyk (2012), González-Aguilera et al. (2013) and Berger et al. (2013)). Parallel to high resolution imagery, data methods of object based image analysis (OBIA) are more and more popular (Weng 2012:43), especially at small-scale applications e.g. infrastructure and settlement development (Wurm et al. (2009), Yu et al. (2010), Dinis et al. (2010), Salehi et al. (2012), Zhou (2013) and Li et al. (2014)).

This study focuses on urban density indices derived from an object based land cover classification. In the following, a selection of indices is analyzed regarding their correlation with LST in an urban environment. The input data as well as a short discribtion of the study area is presented in the next paragraph. Afterwards, the methodology is divided into three parts concerning (i) object based land cover classification, (ii) urban density indices and (iii) correlation analysis. Finally, we try to figure out wether two- or three-dimensional indices improve the correlation results with LST and if specific land use classes affect this relationship.

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3 MATERIALS

3.1 Data source & preparation

The data basis of this study consists of Ikonos, LiDAR and Landsat ETM+ data as well as additional datasets (Fig. 1). The high resolution optical dataset is available for one time step (2005-09-20) and as a GEO-product. Due to missing position accuracy a co-registration had to be done. Afterwards, the High Pass Filter, a pan-sharpening technique was conducted with Erdas Imagine in order to improve the spatial resolution up to 1 m.

A normalized Digital Surface Model (nDSM) was produced by subtracting a digital elevation model (DEM) from a DSM, derived from LiDAR data. The LiDAR dataset is characterized by a point density of 1-4 points/m² and can be used with a resolution of 1 m. A mosaic of orthophotos, resampled with a bilinear method up to a resolution of 1 m, was used for validation. Additional vector data consisting of a land use classification and land cover change time series were provided by the city of Cologne and German Aerospace Center (DLR). The land use dataset, available on block level, provided the basic unit for the correlation analyses and to differentiate between major land use classes.

LST data were derived from Landsat ETM+ for six scenes, covering acquisitions of all seasons, with recordings during day-time between 1999 and 2001 and one night-time image of 2008.

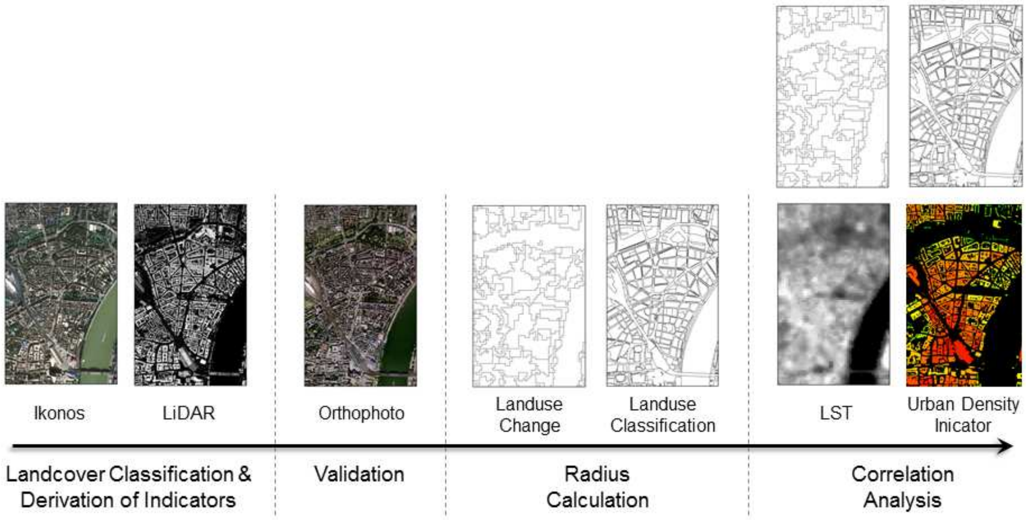

Fig. 1: Data input and methodical approach

3.2 Study area

The city of Cologne is located at the river Rhine in the North-western part of Germany and belongs to the federal state of North Rhine-Westphalia (50°56'29''N, 6°57'28''E). The development of the settlement structure started already in 38 B.C. and was influenced by several circular expansions during the High Middle Ages (Curdes & Ulrich 1997). The historical structures, especially the circular formation of streets around the city centre, are still distinctive elements of Cologne. Today, the city has more than 1 million inhabitants and covers an area of 405.2 km² (IT.NRW 2013).

4 METHODS

In the following chapter, the methodical approach of the main working packages is presented. The derivation of the landcover classification and the adaption of the existing ruleset is described as well as the validiation of the result using orthophotos. Based on a previous landcover product, urban indicies were implemented from a preceding study by Berger et al. (2012) and from further literature studies. Different analyses, concerning the correlation between indicators and LST are discribed in the final part.

4.1 Object-based Classification

The ruleset of Berger et al. (2012), developed for test sites in Erfurt and Rostock, provided the basis for the land cover classification of Cologne and was simultaneously tested in terms of transferability. All working steps of the classification and the calculation of all indices were performed with Definiens eCognition software.

The segmentation is maintained due to better comparability and consists of three processes: Quadtree Segmentation, Multiresolution Segmentation and Multiple Object Difference Conditions-based Fusion. The two segmentations subdivide the Ikonos scene using spectral information and slope as well as height derived from nDSM. The last step aggregates objects, if they meet defined threshold values regarding specific spectral and spatial similarities. Afterwards, the input scene is classified into elevated and non-elevated areas using the height as a parameter and a threshold of 2 m to exclude vehicles and small artefacts from elevated land cover. Basing on this classification, six different land cover classes were identified: Tree, Building for elevated objects as well as Grassland, Water, Bare Soil and Impervious for non-elevated objects. Every single class is defined by single or multiple attributes of nDSM, multispectral information or geometrical properties (Fig. 2). For classes with similar characteristics e.g. Bare Soil and Impervious, the separability was analysed with Box-Whisker-Plots, in order to find specific ranges of attribute values to avoid overlaps and an inaccurate object classification. The classification ruleset of Berger et al. (2013) therefore was adapted and in some cases renewed.

The software Erdas Imaging 2011 was chosen to perform a validation of the classification result by distributing 50 random points per class. As reference data a mosaic of orthophotos from Cologne with a spatial resolution of 1 m was used.

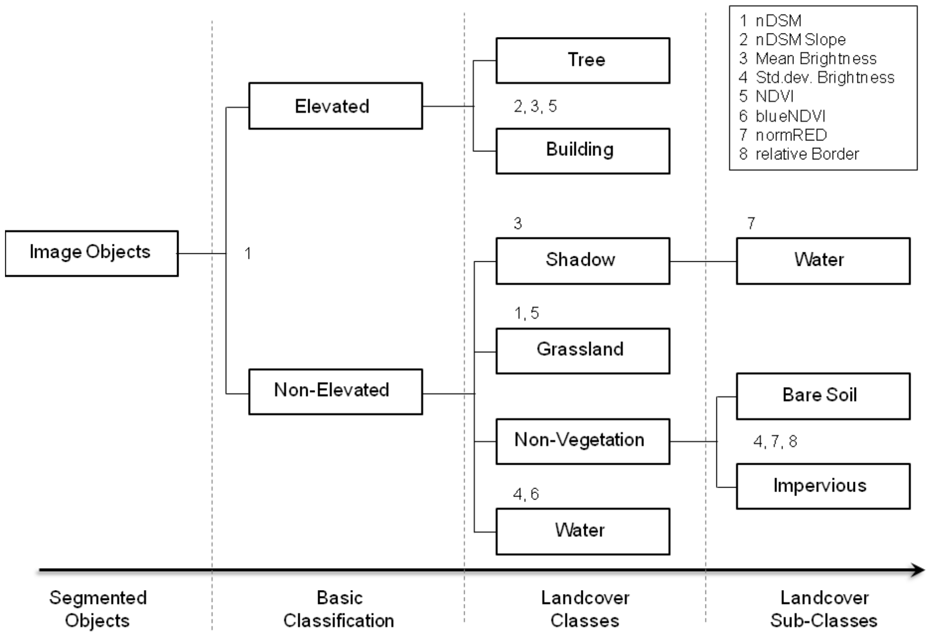

Fig. 2: Derivation of land cover classes and input parameters

4.2 Urban Density

The ruleset of Berger et al. (2013) was provided and extended for derivation of urban indices. The most appropriate indices were considered in the following. For each indicator the result is a map of building objects, where every object contains one indicator value. All of them differ concerning their area of interest (AOI), which can be object or area oriented. In the former case the calculation is only based on the object information e.g. building height and gross floor area. For area related indices the AOI was defined as a specific radius around the centroid of the active building. The radius was set to 100 m for further analyses.

The inverted Floor Area Ratio (iFAR) was modified by Berger et al. (2013) and is an object related indicator, which reflects the ratio of active building area to the sum of all floors. The iFAR takes into account each separate floor by proofing and recalculating each floor individually using the nDSM.

In the following all named indices are related to the AOI. The two normalized indices Impervious Surface Area (ISA) and Vegtetation Fraction (VF) present the relationship between impervious surface or vegetation and the AOI (Lazzarini et al. (2013), Berger et al. (2013)). The Building Aggregation Index (BA) focuses on the arrangement and compactness of buildings within the AOI and contains information about the number of

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buildings within the AOI, median iFAR, median distance between active building and closest one as well as a ratio of building area and AOI (Berger et al. 2013). Both indices, Urban Vegetation Index (UVI) and Vegetation Volume to Built-Up Volume (VV2BV), by Tompalski & Wezyk (2012) are presented in a normalized form in this article. The second one, similar to VF and ISA, takes the third dimension into account and is a ratio of high vegetation volume and building volume. The UVI consist of VV2BV, a ratio of vegetation and building area and a weighted factor of all green and impervious areas. The indicator Urban Density (UD) was published by Berger et al. (2012) and describes the relation of urban development to vertical and horizontal settlement structure with a scale range from -2 to +2 with high values indicating high urban development. Urban Density consists of four independent indices: BA, ISA, iFAR and VF.

4.3 Correlation Analysis & LST metrics

The correlation analysis was performed between all indices and LST data for all block level objects and for specific land use classes. Besides single LST time steps, three different metrics were calculated to improve the regression results. The input data for the metrics: Mean Annual Surface Temperature (MAST), Yearly Amplitude Surface Temperature (YAST) (Bechtel 2012) and Principle Component Analysis (PCA) are listed in the table below (Tab. 1) and were computed within ArcGIS.

	Apr. 2008 (Night)	Aug. 2001	Oct. 2000	Apr. 2000	Jan. 2000	Aug. 1999
MAST	x	x	x	x	x	x
YAST/PCA		x	x	x	x	x

Tab. 1: Input data for LST metrics

5 RESULTS AND DISCUSSION

The classification of Cologne into six different land cover classes is illustrated in figure 3. Buidling objects differ within the study area from compact block development with sparse vegetation in the CBD area (Central Business District) to open block and row development with higher amount on vegetation in suburban settlements and detached houses in periphery zones. The validation of the object based land cover classification achieved an overall accuracy of 91.33 % with user and producer accuracies ranging between 78 to 100 %, where the classes Building, Water and Bare Soil stand out with high accuracy values whereas areas classified as Impervious were characterezied with lower accucary results. Similar validation results of land cover classifications with object based methods also published Wurm et al. (2009) for Cologne and Dinis et al. (2010) for a study site in Lisbon with overall accuracies of 90.12 % and 87 %. Misclassifications occurred between Bare Soil and Impervious classes especially in industrial areas or between Impervious areas and Water in shaded areas on bridges and harbour areas. In the latter case, the Quadtree segmentation caused rough quadratic objects in shaded water areas, which could not be correctly classified because Brightness values do not match the defined classification parameters. The same situtation arose along shore areas, where overlaps of Bare Soil occurred. An improvement of the classification result can be associated with high site specific adjustment of the ruleset.

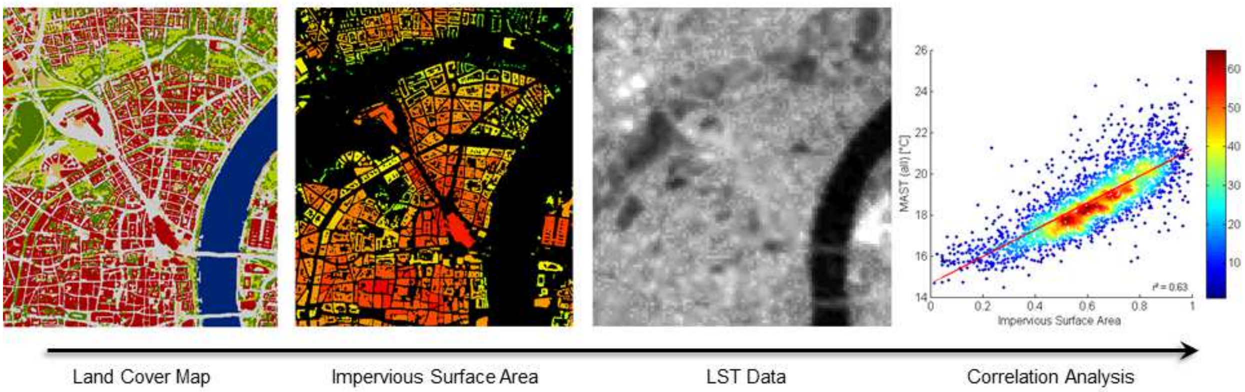

Fig. 3: schematic representation of interim results and final correlation diagram

The results of the urban indices were analysed in terms of spatial distribution and concerning their relationship to LST. In contrast to UD, ISA, UVI and VV2BV do not only indicate a radial behaviour, they also highlight industrial areas and settlements in peripheral regions with high values, indicating urban density. Whereas, using UD and BA only the CBD area is presented with high values with increasing distance UD decreases. The following table 2 summarizes all correlation results of urban density indices and LST metrics. Besides an examination of significance was applied, which confirm the significance of the correlation. The highest correlation results were achieved using the mean value of all LST datasets, MAST or single LST data, recorded between spring and autumn and the two-dimensional indices ISA and VF.

	UD	ISA	VF	BA	VV2BV	UVI	iFAR
MAST	0.69	0.79	-0.82	0.40	-0.77	-0.78	-0.30
YAST	0.50	0.63	-0.67	0.23	-0.62	-0.62	-0.15
PCA	0.62	0.75	-0.78	0.32	-0.73	-0.73	-0.22

Tab. 2: Correlation Matrix of urban density indices and LST

Considering the different land use classes, nearly no correlation was shown for the city area. Only 31 block objects and a very narrow range of indicator values might be the reasons for those results. Whereas, the settlement regions like block and row development, single houses and allotments achieved satisfying correlation results.

6 CONCLUSION

The analysis of different urban indices demonstrate, that three-dimensional indicators could not improve the relationship to LST. Moreover, simple ratios of urban green or impervious areas to the AOI are most suitable to achieve the best correlation results. The UVI and VV2BV indices work like ISA and VF and also consider volume information. Thus, their correlation results are similar to the two-dimensional ones. A mean value of a LST time series could also lead to improvments in this context. Future work will focus on multiple regression models, which might be a better approach to describe the characteristics of LST in urban environments than linear anlyses.

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