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Urban Land Cover Change of Olomouc City Using LANDSAT Images

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Abstract**—**This paper regards the phenomena of intensive suburbanization and urbanization in Olomouc city and in Olomouc region in general for the period of 1986–2009. A Remote Sensing approach that involves tracking of changes in Land Cover units is proposed to quantify the urbanization state and trends in temporal and spatial aspects. It actually consisted of two approaches, Experiment 1 and Experiment 2 which implied two different image classification solutions in order to provide Land Cover maps for each 1986–2009 time split available in the Landsat image set. Experiment 1 dealt with the unsupervised classification, while Experiment 2 involved semi-supervised classification, using a combination of object-based and pixel-based classifiers. The resulting Land Cover maps were subsequently quantified for the proportion of urban area unit and its trend through time, and also for the urban area unit stability, yielding the relation of spatial and temporal development of the urban area unit. Some outcomes seem promising but there is indisputably room for improvements of source data and also processing and filtering.

Keywords**—**Change detection, image classification, land cover, Landsat images, Olomouc city, urbanization.

I. Introduction

MOST of the human activities (labor, manufacturing, education, entertainment...) take place in the cities [1] which is nowadays being rather typical for developed countries where up to 80% of the population lives in the cities. In the second half of the 20th and by the beginning of the 21st century the cities world-wide underwent a rapid growth tightly related to unrestrained exploitation of space, which has brought about numerous problems [22]. Regulation of urban development problematic is being attended by different institutions, on various levels of state and self administration, usually by means of municipal planning [22]. Planning usually takes into account the current and previous states or different states over a period of time, for plotting the possible development scenarios of an area. Therefore, the studies of the state and dynamics of urban development can significantly benefit by using Remote Sensing methods [3] [8].

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They are particularly suitable for localization, spatial measurement and analysis of urbanized areas [2] [10]Traditional visual interpretation of aerial photographs or the field surveys stand in contrast with much faster, more systematic and copious digital image processing techniques. These techniques are superior in terms of data extraction and handling, while still having the same goal as above-mentioned common approaches. On the other hand, the latter are not as temporally limited since they do not require satellite data (such products had not became available before the end of the 20th century), but it could be speculated that the nature of phenomena [22] we are concerning goes in favor of preferring satellite over other resources. In this research we have concentrated on the combination of image processing techniques directed toward extraction of the information that can be used for a successful monitoring and planning-managing of urban areas [6]. The ultimate goal of the study was to identify and quantify particular changes of urban and suburban space that took place in the past three decades (1986–2009) in Olomouc region in Czech Republic.

Similar studies in close surroundings have been recently conducted. A detailed study of changes in Land Use units in sub-urban belt of Brno reviled the higher dynamics of its northern and southern periphery. Another study regarding Moravian Ostrava agglomeration pointed to the very problematic sub-urban development. Unfortunately, most of these researches are still on pre-academic level, presented as diploma thesis throughout GIS departments in Czech Republic. In respect to these previous researches our study adopted but also modified and improved proposed methodological approaches.

A. Study Area

This research regards the Olomouc region, one among the 14 regions of Czech Republic, where regions represent the largest administrative units. More particularly, the emphasis of the research is directed toward Olomouc city, the capital of the region, and settlement that nowadays counts 102 000 inhabitants and spreads over 103 km^2 in area [23]. The development of the region and the city itself came after numerous evolutionary stages, but it is the late 1990's that have paved the trends of the urban development of the city as we know it today. One could also notice that the suburban development, which can be tracked back since the end of the 19th century, is the key factor that shapes the city's structure and dynamics and that actually led the city to a position that it faces today. Namely, non-strategic suburbanization stretched the city borders toward their ultimate landmark frontiers, such as arable land or protected natural habitats (Litovelské Pomoraví). The only remediation that prevails for further city development is strategic utilization of the unused space and re-structuring of the present state.

II. Dataset

Dataset which was used for tracking changes of target Land Cover units in Olomouc region comprised of an assembly of 30 m resolution Landsat TM-ETM images, involving several time splits from 1986–2009, namely 1986, 1990, 1996, 2000, 2006, and 2009. Similar time intervals between them were chosen in order to track the changes gradually. Moreover, all images were taken at early autumn, so that the seasonal variations effects could be maximally suppressed. The resources for the dataset images involved open libraries of Landsat images [24] [25].

The images from all time splits were first registered, where the 2009 time split was chosen as the referent one (due to its closest resemblance to a present state). All other time splits were co-registered with 2009 image on a pixel level. For each frame of each time split 7–8 pairs of referent points were used[5] in polynomial transformations of the second order, to stretch (transform) each frame accordingly to the referent. The resulting Root Mean Square error did not exceed 0.5, i.e. more than 15 m, considering the pixel size.

Visual comparison of 4-5-7 color composite images of the first and the last time split, capturing the Olomouc city and its closest surroundings is shown on Fig. 1.

III. Methods

To unfold the changes in urban/sub-urban development is to analyze their spatial relations with other units, i.e. to analyze the changes of a Land Cover map of the area of interest [15] [16]. In such regard, the methodological framework that has been followed[4] in this research could be split in two separate approaches. They both regarded image processing methods for image classification, resulting in the series of Land Cover maps, which were subsequently used for post-classification change detection [17].

Following the first order CORINE classification [14] and in respect to the expected Land Cover units in our study area, four classes, i.e. arable land, forest vegetation, urban area, and water body, were distinguished per each time split in both approaches.

Pre-processing and processing was performed by combining Idrisi Taiga and Erdas Imagine 8+ packages.

A. Pre-processing Products

In order to make the dataset more convenient for classification, Pre-processed image products were used instead of raw Landsat bands to make a new, Pre-processed set, upon which all subsequent operations took place. In this way the spectral and spatial information reached better efficiency in the classification process. The following image transformations were regarded:

- Principal Component Analysis (PCA) [11] – showed that the highest covariance between 3rd and the 4th Landsat band is in the 2nd Principal Component (PC). This seemed important for extracting vegetation-related differences reserved for the spectra of 3rd and 4th Landsat band.
- Tasseled Cap transformation [18] – gave an apparent match of Moisture layer with actual distribution of water bodies.
- Vegetation Indices – gave several different interpretations of biomass distribution, among which the Normalized Difference Vegetation Index (NDVI) [11] seemed as optimal choice.

Thus, the new dataset, or the Pre-processed set comprised of 2nd PC, Moisture Tasseled Cap, NDVI, and also a 4-3-2 color composite, for every time frame 1986–2009.

B. Unsupervised Classification – Experiment 1

Due to the substantial amount of images to be visually analyzed we herein turned to the automatic procedure of image classification by using K-means algorithm [11] and we named this part of the research Experiment 1. K-means is a clustering algorithm that performs pixel-based classification, i.e. groups similar pixels together in an n-class feature space on the basis of pixel's spectral characteristics [18]. Principally it is sensitive only to the number of desired classes n and the threshold percentage of the stable pixels, which makes it convenient for trial-and-error manipulation in search for the optimal results. Such classification result is still very raw and it needs subtle refinement stage. Good results were achieved easier when the processing mask was introduced. Namely, since our concern is primarily the change of urban and suburban space, we proposed a 300 m buffer zone around the most recent build-up area mask, and regarded only the mask space for change detection analysis. Masking provided less erroneous results of the classification and easier reclassification of raw result. Moreover, we have introduced additional post-processing techniques [7] to Experiment 1. Low-pass frequency filter was used to generalize and smooth the raw classification, i.e. to handle the isolated pixels, salt-and-pepper effects and so on [7].

C. Semi-supervised Classification – Experiment 2

As mentioned above, visual training of an algorithm tends to be demanding and time consuming for the amount of images handled in this research. It would require that every image is sufficiently well classified over training areas by visual interpretation [9]. Herein, we proposed a more effective approach which combines object-based and pixel-based classification techniques in what we have named Experiment 2. Unlike in Experiment 1 we have not masked the area of interest, but rather have challenged the approach in full extent. Some previous researchers [9] have considerably preferred semi-supervised over unsupervised classification, primarily due to reduction of undesired visual effects (e.g. salt-and-pepper). Thus Experiment 2 consisted of object-based classification, i.e. image segmentation [13], followed by supervised pixel-based classification with Maximal Likelihood Algorithm (MLA).

The first stage segmented images according to their spatial and spectral similarity, i.e. it grouped neighboring pixels if they were spectrally similar enough [13]. This also means that the objects of similar spectra, e.g. lake, forest, road, can be represented within the same segment by the algorithm. The segments can be merged further on, depending on the desired generalization level. In our case 1st level of Corine Land Cover map does not require particularly detailed segmentation, i.e. segments can be larger in size, which is why the similarity tolerance was set to 40 – 60%.

Having the image segmented at desired level, training of the MLA took place. Generated segments served as predefined training areas, where each segment represented an object needed to be assigned with one of the four Land Cover units (arable land, forest vegetation, urban area, and water body). In comparison to the standard on-screen training, this procedure tends to simplify the effort by pre-suggesting the training objects. In respect to the average segment size, 100 training examples (roughly 25 per each category) were considered sufficient. Segmentation was performed over the Pre-processed image set, with False Color Composite (4-3-2) as a visual control reference.

The MLA or Bayesian classifier works on the basis of Maximal Likelihood calculated by the Probability Density Function (PDF), which is associated with a particular training site (assembly of training objects). Pixels are being classified according to their posterior probability of belonging to a specific Land Cover unit. Since not all the units/classes are distributed equally in area, we decided to subjectively adjust their weights (prior probabilities) according to their area, so that the largest unit receives slightly higher posterior probabilities than the smallest unit as follows: 0.4 for arable land, 0.3 for urban area, 0.2 for forest and 0.1 for water body. The classification than took place over the Pre-processed set and gave one Land Cover map for each time split.

D. Classification Error Assessment

In order to provide classification reliability, all generated Land Cover maps from both Experiment 1 and Experiment 2 were assessed by error matrix [5] on the basis of specified number of random points. For the purpose of this research 165 control points selected only for urban area class, appeared to be sufficient for error estimation. Control points are inherited from the most recent reference, i.e. from the 2009 time split, as indicated before. This assessment was necessary not only to control the continuity of classification accuracy throughout the different time splits, but also to make preferences and exclusions of erroneous data.

E. Change Detection

Since we preferred post-classification approach [12] [19] for tracking changes the matter of the change detection was rather simple. It came down to tracking differences in consecutive Land Cover maps 1986–2009. Due to the above stated differences in masking techniques in Experiment 1, the statistical change quantization [20] needed to be different. One could regard that Experiment 2 concentrates more generally on Land Cover units change in the entire Olomouc region, while Experiment 1 focuses on urban changes in urban areas. Accordingly, since not entire area was used, only relative areal changes (number of changes) and stability of units are calculated for results of Experiment 1, and their total equivalents for Experiment 2.

IV. Results and Discussion

A. Experiment 1

In terms of visual impression, the quality of the classification was satisfying in all time splits (Fig. 2). Only slight noise effects are apparent in urban area units. Quantitative error assessment claims similar, but it gives slight preference to results achieved by specific post-processing technique. Namely, in Experiment 1 post-processing included smoothening by low-pass filter with 3x3 and 5x5 window widths. Results (Table I) are showing that 3x3 filter has shown the best performance (Fig. 2b), particularly when the urban area class was excluded from the filtering process (Fig. 3).

TABLE I
Accuracy Assessment in Relation to Different Post-processing (low-pass) Filtering

Year	3x3, urban area not excluded	3x3 urban area excluded	5x5 urban area excluded
1986	78.79%	78.79%	78.79%
1990	87.88%	88.48%	87.88%
2000	83.03%	82.42%	81.21%
2006	87.88%	87.88%	86.06%
2009	88.48%	89.70%	87.88%

As for the detection of changes, it is apparent (Table II) that change of urban area unit has had an increasing trend over the 1986–2009 period. It can be speculated that larger unit area in 2006 than in 2009 is problematic to explain, since it actually implies decrease in urban development in 2009. However, it might be speculated that 2006 time split is, perhaps affected by the atmospheric effects in the scene or some other incoherency.

The stability of units (Fig. 5a) further supports the idea of intensified urban area increase during the years, while pointing out which units had got affected by the urbanization and suburbanization process. The results are clearly showing the spatial distribution and intensity of suburbanization, because the majority of unstable pixels (newly created ones) are clustered in close surroundings of the city itself, rather than within it (Fig. 5a).

TABLE II
Trend of Urban Area Unit Progression through Time (Experiment 1)

Year	1986	1990	2000	2006	2009
Area (km^2)	28,26	38,40	44,19	58,00	51,68

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B. *Experiment 2*

Since operating with the full extent, this experiment had more problems with accuracy, and the initial reach of accuracy (peeking at 85% for urban area unit) was not improved by the post-processing filters, so "raw" Land Cover maps with roughly 75–85% of accuracy for urban area unit were adopted. This had been apparent for all time splits, but 2000 and 2006 were particularly problematic. A cross-tabulation gave a good insight in the unit distribution through time. Expectedly, the highest differences appeared between the 1986 and 2009 Land Cover maps (Fig. 4) depict these differences visually. Since the emphasis is on the urban area change, analysis of urban area unit relations in different time splits was extracted from cross-tabulations. The area of the urban unit is in rising trend, but some irregularities are apparent (Table III). Note that the trend proportion is quite similar with the results of Experiment 1 (Table II). Since it is unlikely that the urban area size decreases drastically from 2006–2009 (Table III) and also due to noticeable overestimation of urban area unit in Land Cover map for 2006, we can assign these irregularities to the classification error. The classification was troubled by very subtle spectral difference of arable land unit and urban area unit, which is why in some cases (2000 and 2006) the overestimations of urban area is drawn on behalf of the arable land unit.

TABLE III
TREND OF URBAN AREA UNIT PROGRESSION THROUGH TIME (EXPERIMENT 2)

Year	1986	1990	2000	2006	2009
Area (%)	11.28	11.69	12.88	15.63	12.57
Area (km^2)	11.84	12.27	13.52	16.41	13.20

When it comes to unit stability, two cases had been concerned, the one which regarded only direct differences between 1986 and 2009 Land Cover maps, and generic stability of units which took into account all transitive time splits (1990, 2000, and 2006).

The first case (Fig. 5b) successfully estimated suburbanization in the Olomouc city, depicted by development of peripheral settlements especially on the western and eastern outskirts of the city. Highway and supplementary infrastructure is also well presented. The drawback is likely overestimation in smaller settlements, i.e. villages west from the city, since the field evidence does not imply to such a strong village expansion. Stable pixels are contouring the existing settlements, Olomouc city core etc. but interference of some other units (such as vegetation or arable land) is present. The later particularly affects Olomouc, since the MLA classifier could not distinguish among city parks or gardens on one side and vegetation or arable land on the other. The latter is most probably the reason of existence of considerable amount of extinct pixels of urban area unit within the city itself.

The second case initially faces the problem of classification error within urban area unit, followed by above mentioned problem of urban area and arable land relation in transitional time splits. Expectedly, the biggest problem was less precise estimation of new areas, so that it can be generally concluded that the analysis followed the trend (especially considering the road infrastructure) discovered in the first case (Fig. 5b) but to a lesser degree. The advantage is more subtle estimation of rural settlement development (villages west from Olomouc). However, the interpretation seems timid and inconclusive because of chaotic distribution of pixels, apart from the stable unit class. It is also shown (Table IV), that despite such visual impression, the second case tends to overestimate all classes apart from stable unit, which goes in favor to the previous statement.

TABLE IV
DISTRIBUTION OF URBAN AREA UNIT STABILITY EXPRESSED IN AREA PERCENTAGES

Unit	Non-urban area	Extinct urban area	Stable urban area	New urban area
1986 & 2009	81.30%	6.14%	5.14%	7.42%
1986–2009	66.53%	20.90%	2.26%	10.31%

V. CONCLUSION

Presented topic is yet to be elaborated in detail, since it troubles cities not only in Olomouc region, but elsewhere in Czech Republic. This research is just one contribution with an angle that emphasizes tracking of changes within technologically limited period of past three decades. However, the nature of the urban development overlaps with this period, which justifies the implemented approach. As presented before, classification using different techniques and tactics in Experiment 1 and Experiment 2 gave more or less reliable results, implying rising trends of urbanization. The result comply in trends, perhaps more than in shear figures, pointing particularly at extent of suburbanization in Olomouc city, but also developments in smaller settlements around. Road infrastructure seems to be well delineated and stable units truthfully discern old city core of Olomouc and centers of other smaller settlements. However the drawback has been evidenced in several time splits, and it primarily regarded classification error. Namely, some time splits were troubled with slightly different source Landsat images and it could be speculated that it caused different responses in proposed classification techniques in both experiments. We can conclude that whether unsupervised or semi-supervised classification performed similarly and faced common problems in both experiments. Good potential is seen and confirmed in merging object-based and pixel-based classification in Experiment 2.

Having all the benefits but also all the drawbacks in mind, the room for improvement mainly reflects in more cautious preparation stage, advanced atmospheric corrections, calibration of images, in order to align all transitive time splits to the same standard. This would provide higher quality of inputs, and presumably, better outcomes of the classification. Another point is post-processing which initially gave some small improvements to the accuracy, particularly in Experiment 1, and perhaps, following that lead could better the overall reliability of the analysis. Otherwise, the results could only be improved by full implementation of visual analysis as proposed in CORINE standard for instance, or even to scale-down the research and use aerial photos or high resolution panchromatic images to magnify the changes, or to combine it with night time images [21]. Consequently, it would rise time-consumption and cost of the research, which stands in contrast to the conveniences we have presented with our approach.

APPENDIX

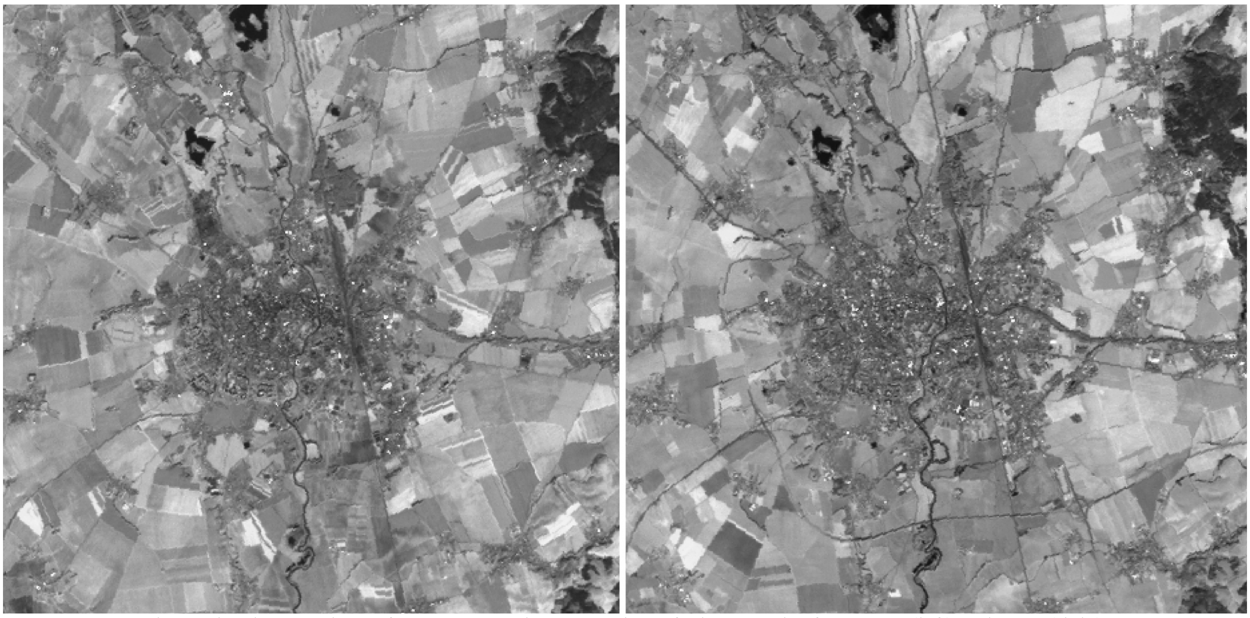

Fig. 1 Visual comparison of RGB 4-5-7 color composites of Olomouc city from 1986 (left) and 2009 (right)

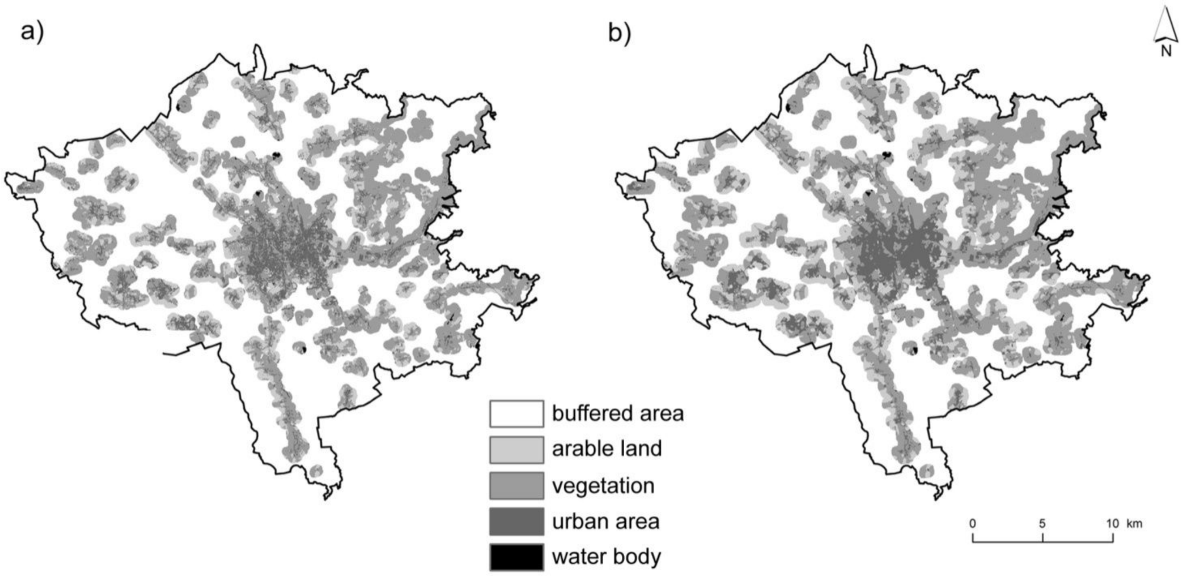

Fig. 2 An example of Experiment 1 Land Cover map (buffered) from 2009 a) before, b) after applying post processing filter (low-pass 3x3)

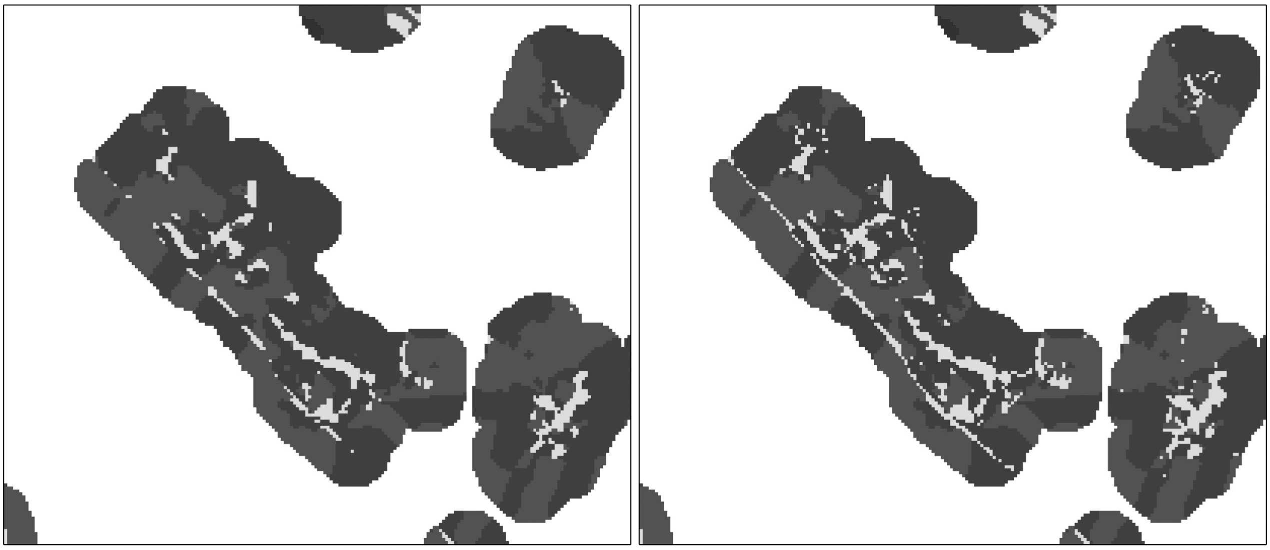

Fig. 3 A detail of the filtering effect: on the left, a small settlement with obscured road infrastructure in the 2009 Land Cover map (Experiment 1) after implementation of 3x3 smoothening filter, and on the right, the same scene but after implementation of 3x3 smoothening filter with exclusion of urban area class in the filtering process

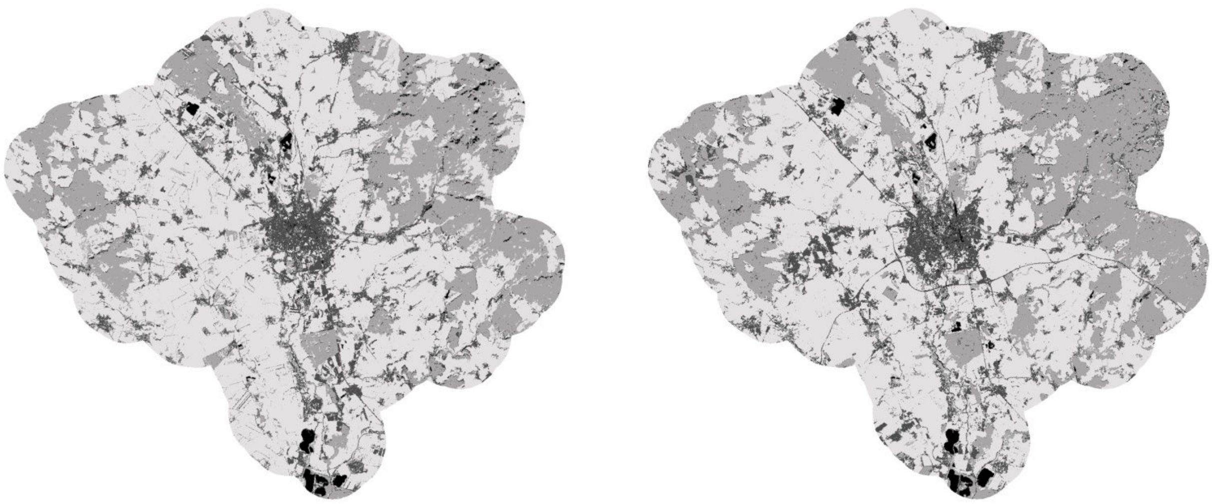

Fig. 4 Land Cover maps of Experiment 2: a) Land Cover of 1986 time split, b) Land Cover of 2009 time split

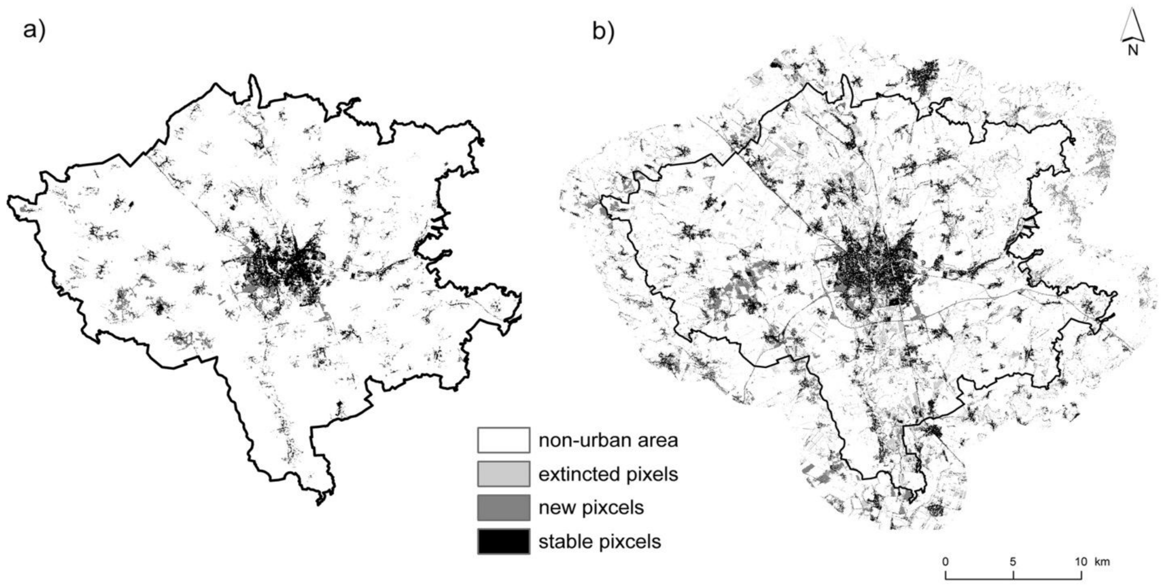

Fig. 5 Comparative image of 1986–2009 pixel stability of urban area unit: a) Experiment 1, b) Experiment 2 with only 1986 and 2009 time splits (no transitive time splits from 1990, 2000 and 2006)

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