MULTI-LEVEL SEGMENTATION OF SOIL SEALING IN URBAN AREAS

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ABSTRACT: Urban development presents the greatest driver of soil loss due to sealing in urban areas by buildings, pavement and transport infrastructure. The ability to monitor soil sealing is crucial to understand urban ecosystems and their changes. In the present work we used high-resolution satellite images Worldview-2 over urban areas in Ljubljana, Slovenia, which were analyzed using object-based classification method. We focused on segmentation step where different segmentation parameters were chosen, each one adapted to best suit the characteristics of the selected land use (buildings, sealed and unsealed areas). The output of the approach is not a single partition, but a multi-level of regions. The need for multilevel segmentation approach comes from the practical experiences of extracting objects from satellite images, since it is difficult to determine a single (uniform) scale or level appropriate for the variety extraction of objects of interest. This paper compares three "fine" single-scale segmentation results with one "coarse" segmentation and reference data over same urban area using commercial software that does not offer multilevel segmentation. The experimental results show that the proposed multi-level approach produce more accurate results compared to "coarse" segmentation method, in terms of visual and quantitative evaluation.

1. INTRODUCTION

1.1 Segmentation

Landscapes are complex systems composed of a large number of heterogeneous components that interact and exhibit adaptive properties through space and time. Therefore to fully understand, monitor, model and manage our interaction within landscapes we need suitable remote sensing data, methods capable of identifying pattern components and the ability to link and query these objects within appropriate hierarchical structure (Hay et al., 2003). With the higher use and accessibility of high spatial resolution imagery object-based image analysis (OBIA) was developed. This methodology works in the similar principle as human brain functions where high detailed image is segmented into homogeneous regions called segments or "image objects" (Benz et al., 2004). Segmentation is the most important step within the object-based approach, so it is important to evaluate image segmentation quality to identify good segmentation parameters. One widely accepted definition of what constitutes a good segmentation for highly-textured and natural images is one in which regions are uniform and homogeneous and where regions are significantly different from neighboring regions (Haralick and Shapiro, 1985, Zhang et al., 2008).
While choosing segmentation parameter adequate for only one particular land use, others are usually under- or over-segmented. These under- or over-segmented regions are then refined by further segmenting under-segmented regions at finer scales and merging over-segmented regions with spectrally similar neighbors. Issues related to over- and under-segmentation are the main disadvantages of using only one segmentation scale for remote sensing images, and why using a multi-level approach may often be preferable (Johnson and Xie, 2011). Like authors Hay et al. (2003) comment there is no single "optimal" scale for analysis of remote sensing images, rather there are many optimal scales that are specific to the image-objects that exist within a scale. OBIA is therefore inextricably linked to multi-level analysis concepts. Objects appear at different scales of analysis in the same image (Bruzzone and Carlin, 2006, Blaschke et al., 2000, Hay et al., 2003, Carleer and Wolff, 2006) therefore multi-level hierarchical segmentation methods are needed in VHR image analysis and applications (Baatz and Schape, 2000, Tilton, 2003, Carleer et al., 2005, Akcay et al., 2008).
It is thus surprising that overall number of papers reporting on multi-level segmentation methodology to map urban areas is relatively small. Multi-level approach where a hierarchy of several single-scale segmentations were created by authors Hay et al., 2003, Trias-Sanz et al., 2008, Corbane et al., 2008, Zhou and Troy, 2009. Li et al., 2011, have presented a multi-level segmentation method for urban impervious surfaces using VHR imagery, also Johnson and Xie, 2011, did research of the use multi-level approach of a high spatial resolution over residential area.

In this study we created several segmentations of dense urban area consisting of segments generated first at one general, “coarse” segmentation. Later we extracted image objects using different levels of segmentation detail at three “fine” segmentation scales. Doing this we were able to adapt segmentation parameters to the characteristics of the belonging urban land cover class: sealed area, unsealed area and buildings. While using multi-segmentation effects by combination of three single-scale segmentations over and under-segmentation are generally reduced. One problem with visually identifying best segmentation parameter is that this method can be highly subjective, as different people may have a different view about what the best segmentation is (Paglieroni, 2004).
We have to point out that by multi-level expression in the article we focus not only on scale, but also on level of adjustment of the segment or the purpose of extraction. It is the relationship between segment and merge level, through which appropriate level of processing for each land type is defined.

1.2 Soil sealing

Soil sealing is defined as covering of the soil surface with impervious materials as a result of urban development and infrastructure (JRC, 2010). Impervious surface has been recognized as an important indicator in urban environmental assessment and a valuable input to planning, management activities and urban ecological applications. Remote sensing has proven useful to provide spatially explicit information on urban areas, although spectral information is limited and a high degree of user interaction is required for delineating impervious land cover classes (Van der Linden and Hoster, 2009). The sealing of soils under cities would in turn modify the local climate, leading to even higher temperatures. The differentiation of the city climate is most evidently manifested in the increase of temperature of the air close to the sealed soil relative to the air temperature outside the city, what we call after Howard (1833) “the urban heat island” (Scalenghe et al., 2009). Therefore unsealed spaces will play a crucial role in supporting urban ecosystems, a fact recognized in public policy commitments. The increase in artificial surfaces in the last decades was not due to the increase in population in most of the countries, but rather to changes in population behavior (shift from an intensive to an extensive urban pattern: suburbanization) (Scalenghe et al., 2009).
A detailed description of three major elements of urban heterogeneity – vegetation, buildings and sealed areas – is required to facilitate a deeper understanding of relationships in the coupled human – natural urban system (Cadenasso et al., 2007). This information is needed at different levels of detail and at various scales.

2. STUDY AREA AND DATA

2.1 Study area

The research was made on a part of a residential area in the city center of Ljubljana, on approximately 1700 m x 1000 m subset extracted from WorldView-2 satellite image (Figure 1). This subset represents dense and highly fragmented urban area. The land cover types in the area include trees, grasslands and impervious surfaces (buildings, roads), so different types of land cover can be found within a small area. There is main Ljubljana’s park Tivoli seen on western part of the image, the railway station in the image center and rich road network going through the city center.

Figure 1: Location of the study area: the city centre of Ljubljana.

2.2 Data sets and software

For this study we used high resolution Worldview-2 image with 8 spectral bands and a panchromatic band acquired on 10th of August, 2010. Because of the topographical variations of the Earth surface satellite image was ortorectified using digital elevation model (DEM) in order to remove distortions due to viewing geometry. With the intention to use higher spatial resolution and keep the multispectral information an eight band pan-sharpened multispectral image with pixel size of 0.46 m was created using the Gram-Schmidt spectral sharpening technique.

ENVI EX Feature Extraction module has been used to process the data. This software does not support multi-level (hierarchical) segmentation.

3. METHODOLOGY

3.1 Image segmentation

In this study, supervised segmentation is used to obtain segments from residential area in Ljubljana, Slovenia. In ENVI EX Feature Extraction module user needs to define two segmentation parameters: segment and merge level. Their combination influences an average size of segments produced by segmentation (segmenting and merge level parameter. Changing these two parameters and their ratio affects the size and the number of segments produced by the segmentation, thus allowing an image to be segmented at different scales. Both values range from 0.0 (finest segmentation) to 100.0 (coarsest segmentation; all pixels are assigned to one segment).
All together four image segmentations were performed using different segmentation level parameters. Since ENVI provide a toolset offering only single scale segmentation, which may represent limitations for some applications, the idea was to adapt one general, “coarse” segmentation for the whole image. Next, more specific, “fine” single-scale segmentations for the three different land uses (buildings, sealed and unsealed areas) were applied. A segmentation using a specific set of parameters for a particular land cover was proposed because the practical experiences showed not all segmentation parameters work well for all land cover types on the same image. Landscape typically consists of different types of land cover that also vary in size (e.g. trees, roads, and buildings). Therefore it may not be possible to properly segment all features in a scene using single scale segmentation parameters. Consequently, an over-segmentation (producing too many segments) often occurs (Johnson and Xie, 2011). Spatial, textural, and contextual information extracted from over-segmented objects is not very useful for the classification in object-based approach, as well as under-segmented objects apprehend little value since they contain more than one class (Liu and Xia, 2010).

3.2. Image classification

Initial segmentation aimed to outline homogeneous regions at one “coarse” spatial scale. The segmentation parameters adopted to well represent all three general land cover types (sealed, unsealed areas and buildings) were identified at the ratio: 29 (segment level) – 85 (merge level). For the “coarse” classification level, segmentation parameters had to correspond to an average shape of any land cover segments, not adapting any particular land cover. The objects extracted during the segmentation were then classified using Support Vector Machine (SVM) classifier in an object-oriented framework along with user selected training sets. The training was performed by operator that is familiar with the study area. All eight spectral bands were used and given equal weight for image segmentation and all available attributes were calculated for all segments. Entire procedure took all together around 2.5 hours for a single case.
The same process was later performed for each of single, “fine” land use segmentation. We performed single-scale segmentation three times, each time we adapted segmentation parameters to specific land use: buildings, sealed and unsealed areas. Best performing segmentation parameters are shown in Table 1. Nine land cover classes were used all together: *Sealed areas, Roads, Railways, Buildings_red, Buildings_grey, Buildings_light, Trees, Meadows and Shadows*. All of the segmented images were then exported as polygon shape files for further analysis in ArcGIS. Features smaller than 4 m^2 on the ground were ignored even though they could be seen (i.e. small individual trees, small areas of shadows, chimneys).

3.3. Optimal segmentation parameters

For the fine level, segmentation parameters were each time adapted to the land use we focused on. In the Table 1 one can see that parameters are varying depends on which land cover we have focused on. Vegetated areas were equated to unsealed soils, and non-vegetated surfaces were equated to sealed soils.

	Segment level	Merge level
General “coarse” segmentation	29	85
“Fine” segmentation – sealed areas	37	60
“Fine” segmentation – unsealed areas	38	80
“Fine” segmentation – buildings	27	87

Table 1: Single-level segmentation parameters used in each segmentation case.

Class sealed areas (sealed areas as asphalted and pavement areas, main roads and railways) give visually best result while choosing combination of segmentation parameters at 37-60. To obtain unsealed areas (vegetation – trees and meadows) we had to select combination of parameters (38-80) that gave fewer details. The most details were needed for obtaining class of buildings, thus applying segmentation parameters at 27-87.
Also bottom-up approach of selection of land cover classes support necessity of multi-level methodology. While choosing sub-classes when selecting examples regarding their similar spectral signature inside the same land cover class we subdivided one class into many more (e.g. instead of selecting only class "buildings" we selected three subclasses "*Buildings_red*", "*Buildings_grey*" and "*Buildings_light*"). This gave us better results than using only one general class. Although roads are treated as sealed areas we used separate class due to its characteristic geometry (elongation) that is different from other types of sealed areas (i.e. parking area). All subclasses we selected tend to have similar spectral characteristics. Objects can be later joined into dominant ones in post-classification procedure.

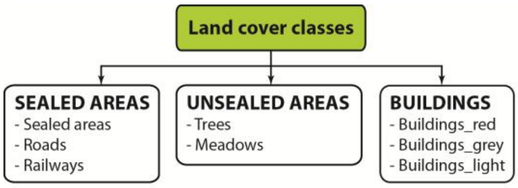

Figure 2: Classes and subclasses used in the classification.

Shadows and building displacements on the image are the consequence of the heights of the buildings and the position of the sun in the time of acquisition. Both phenomena counteract to reliably delineate spectrally sealed and unsealed areas based on multispectral information. Because of the effect of building displacement facades of higher buildings are viewed and classified as sealed areas.
Polygon boundaries of classified segments were compared to reference data, DTK 5 which is a state topographic data. The reference dataset contains graphic and attribute data on topographic objects in scale 1: 5.000 and are acquired manually by digitalizing DOF.

4. RESULTS AND DISCUSSION

Objects obtained from "coarse" classification results were first compared to objects from "fine" classification result and later to reference data DTK 5. For a comparison attribute "*formfactor*" was used which is a measure that compares the area of the polygon to the square of the total perimeter. This attribute allows a straight comparison between segmentation results and reference data in terms of determine specific spatial scales through shapes of segments. The segments most similar to the reference digitalization shape are determined to be the optimal segments. This attribute is by default calculated in the ENVI software, for reference data we had to calculate it afterwards. The form factor value of a circle is 1, and the value of a square is Π/4 and it is defined by the following formula:

$$formfactor = \frac{4 \cdot \prod \cdot area}{perimeter^{2}} \quad (1)$$

We can assume that building and road segments should have value similar to square and vegetation similar to circle. Since reference data don't offer polygons of vegetation and paved areas in such details as we obtained it from the object-based classification of WV 2 image, these two classes were compared with reference data only visually.

	Building 1	Building 2	Building 3	Building 4	Road 1
Coarse segmentation	0,19	0,31	0,07	0,06	0,02
Fine segmentation (sealed areas)	0,07	0,17	0,07	0,06	0,02
Fine segmentation (unsealed areas)	0,19	0,17	0,10	0,07	0,04
Fine segmentation (buildings)	0,24	0,22	0,12	0,07	0,04
DTK 5	0,34	0,77	0,21	0,12	0,12

Table 2: "*Formfactor*" values of different segments in comparison with reference data.

In the table 2 we can see values of selected attribute for four different buildings and one road. In the case of buildings it is obvious that value of fine segmentation where parameters were adapted to buildings fit better to reference data DTK 5 than other cases. We can see that also visually on the Figure 3.

Figure 3: Visual comparison of same building (Building_2) analysed with different segmentation level parameters.

Since roads in reference data are represented as lines, buffer was calculated in order to obtain polygons that can be compared with the road segments. Here "*formfactor*" was not realized to be appropriate attribute for segments evaluation. Classified roads have more details (e.g. holes from white road lines in the middle) while reference data has no such details and this attribute values can therefore be wrongly interpreted. Instead visual examination of this class was performed. Roads are better segmented using the "fine" segmentation for sealed areas. While segmenting vegetation shapes of trees in the Tivoli Park are best represented when using "fine" segmentation for unsealed areas. In this segmentation we could obtain shapes of few separate tree crowns and small patches of meadows but larger groups of trees were still not under-segmented. Described situations can be seen on Figure 4.

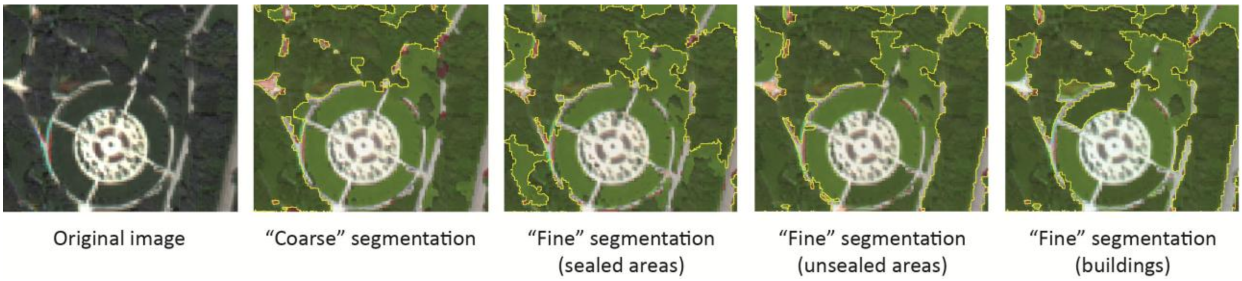

Figure 4: Visual comparison of same vegetation area analysed with different segmentation level parameters.

Summarizing visual examination with the comparison values of some of the attributes of segments we could prove that each land cover was best geometrically represented when segmentation was adapted to specific land cover. This holds also when comparing to polygons of general segmentation or reference data. Resulting image-objects show that differently sized landscape components demand different segmentation parameters and therefore different results. On the other hand, this single-scale approach does not enable establishment of semantic link between obtained image objects, so no object relationship between different levels of land cover details can be established.
However, our findings show that the proposed methodology prove the need of multi-segmentation methodology while using object based classification as single-scale segmentation methods brings limitations. That means that object based applications should implement multi-segmentation methodology for relevant outputs.

5. CONCLUSION

In this study we have employed a multi-level object-based approach, creating specific four single-scale segmentations. Segmentation parameters were adapted to general classification of land cover and three specific land covers we classified (sealed, unsealed areas and buildings). Significant amount of exploratory work was required to define appropriate segmentation levels since unique segmentation solution is usually not operational. Comparison of "coarse", "fine" segmentation and reference data shows that identifying and refining under- and over-segmented regions can improve global segmentation results.
In future studies we will test how more than one segmentation parameter per each land cover works in order to perform more objective results of segmentation. That means we will use segmentation parameters at various scales by varying scale factor over the whole range of possibilities. This can give us the knowledge which of the segmentation parameters fits better with geometrical attributes of reference data and also less subjective influence would be included in the procedure.
We conclude that the multi-level and multi-scale segmentation approach is a methodology that leads to a better understanding and characterization of the processes, operating through the broad range of scales that form landscape. Although there have been many image segmentation methods developed for remote sensing in recent years, new and more sophisticated segmentation methods are still required to produce more accurate segmentation results for land cover classification and object identification, especially on a fine scale.

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