APPLICATION OF OBJECT BASED APPROACH TO HETEROGENEOUS LAND COVER/USE

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ABSTRACT:

While analyzing satellite or aerial images different inconveniences can have negative effects on final classification accuracy. The objective of this paper is to expose the problems that were faced while classifying land use and land cover over two study areas in Slovenia. Two differently covered areas were chosen intentionally; the intensive agricultural area of Gornja Radgona in North-Eastern Slovenia and the subalpine area of Kobarid in the Western part of the country. By using object based image analysis we focus on two main problems; reducing negative effects of shadows on the image and misleading delineation of spectrally similar classes.

Shadows that are present in the image and inconvenient for the interpretation were divided into two groups; small patches of shadows, which are result of higher objects, and bigger areas of shadows in the mountainous area. Both types of shadows are the consequence of the "inappropriate" position of the Sun at the time of acquisition and significant altitude difference over a relatively short distance. Another issue in the classification process is the delineation of segments that separate classes with similar spectral signature in the segmentation phase. Although segmentation parameters have been optimally set on a value where spectrally similar classes can still be separated, the delineations of classes do not always show the real situation.

This paper presents approaches that were used to minimize both aforementioned problems and through which higher final classification accuracy was obtained.

1. INTRODUCTION

The demand to automate image analysis in operational environments is constantly growing. Object based image analysis, which became an area of increasing research interest in the late 1990s offers an effective method for a good understanding of the Earth's surface, especially on the high resolution (HR) images. Due to the occurrence of a large number of small objects all creating high contrast on HR imagery pixel based change metrics fail to operate successfully (taken from Wulder et. al, 2008, p. 355, Im and Jensen 2005, Niemeyer and Canty, 2003). Object based image analysis consist of two stages: contextual segmentation, where segments (objects) that have information related to shape, site and spatial relation (context) of the objects of the scene are created, and classification, where all created objects are analyzed and classified to the most representative class of land use/cover. It is important to explain here that with object oriented classification we are dealing with two concepts of objects: an *image-object* that is a discrete region of a digital image that is internally coherent and different from their surroundings, and that potentially represents – alone or in assemblage with other neighbours – a *geo-object* (Castilla and Hay, 2008).

Although object based approach offers good final results with its fast, consistent and less subjective monitoring it still presents some disadvantages, especially in the stage of segmentation where creating correct shape of the image-object is desirable. One problem with object based classification is that there are no real objects recognised, but image objects, which can be spectrally confused. It is important to note that the accuracy and the significance of the final measurements, numbers and statistics directly and actually critically depend on the quality of segmentation (Baatz et al., 2008). Considering the large number of existing segmentation algorithms and their versatility (e.g. Guigues et al. 2006; Baatz and Schäpe 2000; Jung 2007; Hay et al. 2003; Pal and Pal 1993 Zhang 1997), the choice of an appropriate segmentation algorithm must rely on objective methods to assess segmentation quality (Radoux and Defourny, 2008).

When segmenting and thus creating object shapes it is important to consider two aspects: 1) the appropriateness of an object's delineation (match of extend and shape with real situation) and 2) the precision of boundary delineation (match with scale applied) (Lang, 2008).

Segmentation can be especially problematic in areas with low contrast or where different appearance does not imply different meaning. In this case the outcomes are represented as wrongly delineated image objects. Therefore, legend may include classes whose instances can barely be differentiated from each other in the image. The possibility exists that the boundaries of the classified image objects do not lead to an agreeable representation of real objects. This implies that there will be some classified image objects that need to be split or reshaped in part of their perimeter – the less clear the relation between two similarities, the more likely the possibility (Castilla and Hay, 2008).

In general, shadows represent a great problem in remote sensing and symbolize a factor that considerably influences the results. Shadows increase the variability of the spectral response of a given feature and complicate the task of separating desired feature classes. One of the most descriptive characteristic is their low brightness.

Shadows have been recognized as important determinants of canopy biophysical characteristics for many years (Richardson et al., 1975). Combinations of some factors (leaf, canopy or landscape levels) result in spatial variations of apparent shadow as observed from remote sensors (Gerard and North, 1997). In fact, changes in shadowing allow some remote sensing approaches, such as with multiangle observations, to estimate the structural attributes of ecosystems (Diner et al., 1999;

Gobron et al., 2000). Therefore, shadows are elemental to be considered in vegetation and urban analysis.

This paper presents empirical solutions that were performed while confronting the disadvantages of object based classification applied to high resolution imagery. Section two introduces the study area, data source and software used in this study and describes the methodology that was used to classify land use/cover. It is explained how issues faced during the procedure of classification were minimized and how the parameters were adjusted to obtain the optimum delineation of image objects during the phase of segmentation. In section three the conclusions are presented and discussed.

2. METHODS

2.1. Study area

In this research two study areas with different geographical settings and land cover/land use were considered. The first study area is intensive agricultural area of Gornja Radgona, located in North-Eastern Slovenia, and neighbouring city Bad Ratkersburg in Austria. The second study area is situated in the predominant mountainous, subalpine area around Kobarid in the Western part of Slovenia (see Figure 1).

Figure 1: Location of the study area.

In both study areas classification of complete land cover/use using object based image analysis was made. In the case of Gornja Radgona area, where about 56% of the total area is rural, also a detailed analysis of agricultural land was done.

2.2. Data and software

The data used in this research consist of orthorectified aerial photographs with a 0.5 m spatial resolution acquired in the summer of 2006.
Object based classification was first performed only on aerial imagery, but since it was limited on only three spectral bands (RGB), we later added the fourth (near infrared) SPOT band. The SPOT image of 10-m spatial resolution was acquired on July 19, 2007. The resulting combined image (3+1) appeared to be the best choice for the classification; SPOT image was not fully used due to its inferior resolution compared to the orthoimage.
The Agricultural Land Use Map (ALUM) of the Ministry of Agriculture, Forestry and Food of Slovenia is used for selection of training classes and validation of results. This map was made

for agricultural inventory and management in Slovenia in 2008 and it has a typological division of 25 separate categories (agricultural and others) of land use in total in scale 1: 5.000. ALUM is a rich source of detailed information on land condition.

The data used in the present work has been processed with ENVI EX Feature Extraction module.

2.3. Results and discussion

With the used software we get to the final results in two stages. In the first step the segments are created from spectral signature of the image (segmentation), which are later analyzed and classified to the belonging classes (classification). This means that the created objects to a large extent influence the classification results and that selecting a proper segmentation parameter is an important knowledge based process. The segmentation algorithm implemented in ENVI is edgebased and employs two parameters that allow users to tune the segmentation outputs (segmentation and merge parameter). The segmentation parameter defines how the image will be partitioned into segmets by grouping neighbouring pixels with similar feature values and by selecting a merging parameter one can define how small segments will be aggregated within larger, textured areas (ITT, 2009). In the two study areas user-specified segmentation parameter was different due to diverse land cover/use in the selected area (see Table 1).

Study area	Segmentation parameter	Merge parameter
Gornja Radgona and Bad Ratkersburg	65	80
Kobarid	40	65
Gornja Radgona (classification of masked agricultural areas)	65	96

Table 1: Values of segmentation parameters used in the ENVI EX Feature Extraction module.

After defining segmentation parameters the operator has to select potential training samples for a classification by visual interpretation in our case. Samples were identified by representative training areas of each land cover it most closely resembled. Whenever possible, approximately the same numbers of representative samples were selected for all classes throughout entire image although this rule was sometimes out of the question as some classes of land use/cover are more frequently present in the area than others. The more features and training samples were selected, the better results were obtained. All object classes were subdivided into ten land use/cover classes in Gornja Radgona and into eight classes in the area of Kobarid (Table 2). Although some classes actually represent the same type of land cover we divided them into more detailed structures due to their different spectral reflectance (i.e. green crops – crop residue and soil, young vineyard – old vineyard).

Gornja Radgona	Kobarid
Road	Road
Building	Building
Grassland	Grassland
Overgrown grassland	Overgrown grassland
Trees and scrubs	Trees and scrubs
Water	Water
Young wineyards	Orchard

Old vineyards	Bare earth – rock
Green crops	
Crop residue and soil	

Table 2: Classes defined in two study areas.

Potential training sites were used as input samples for a supervised classification. Different attributes were considered as an input for classification (ITT, 2009):

- spatial (area, length, compact, convexity, solidity, roundness, elongation …),
- spectral (minimum, maximum, average value and standard deviation of the pixels),
- texture (average data range, value, variance and entropy of the pixels) and
- colour space and band ratio attributes (band ratio, hue, saturation, intensity).

Once a classification image was obtained, the procedure of post-classification followed. First, *clump* and *sieve* filters were applied to the result. These filters are used for the generalization of classified images. Obtained generalized raster was later exported to polygon vector files in the ArcView Shapefile format to correct some polygons where minimum mapping unit dependent on the specific thematic categories was considered.

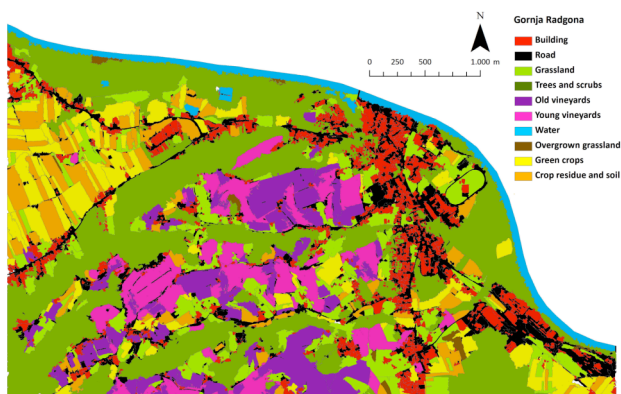The final maps for both study areas are depicted in Figure 2, 3 and 4.

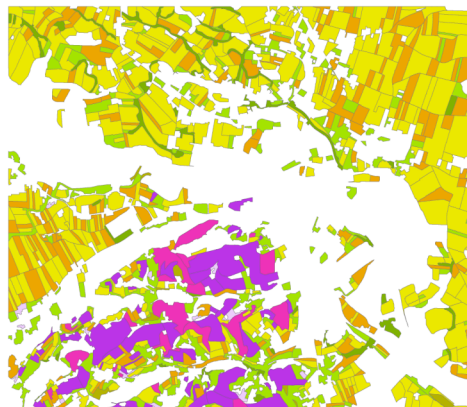Figure 2: Original and classification image of Gornja Radgona.

Figure 3: Final map obtined while classifying agricultural land cover/use of Gornja Radgona and Bad Ratkersurg.
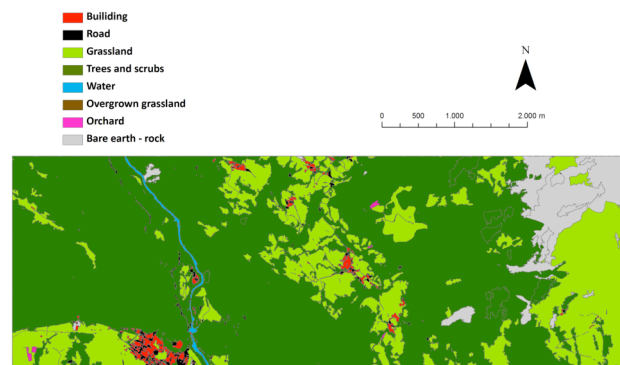

Figure 4: Original and classified images for Kobarid area.

The validation of the classification process was performed by comparing classified data with reference data and producing a confusion matrix. There was also some visual inspection done, not only for the quality of class assignment but also to control the way of delineating the calculated segments.

An ALUM map at a scale 1:5000 was used as a reference land cover map. While ALUM has more divided categories of land use/cover classes, some classes were merged together to obtain the same number of categories as in the case of classification. The updated reference database was thus composed of seven categories. Since ALUM does not separate between urban land cover/use in more detailed classes, "buildings" and "roads" classes were merged into the class "urban area" for the purposes of classification validation assessment. It should be stated here that a direct comparison of classification results with reference data is limited for the following reasons:

- difference in resolution between classification and reference data,
- co-registration errors,
- the fact that the reference data ware acquired later than the classification image.

All the aforementioned facts mean that the total accuracy can never reach 100%.

Then followed the overlay procedure to compare the results. The overall accuracy of the final map was 77.0% for Gornja Radgona, 87.1% for Gornja Radgona while classifying detailed agricultural classes and 91.3 % for Kobarid. The classification accuracies are listed in the Table 3.

Study area	Overall accuracy	Kappa coefficient
Gornja Radgona	77.0%	0.71
Kobarid	91.3%	0.82
Gornja Radgona (classification of masked agricultural areas)	87.1%	0.81

Table 3: Classification accuracies.

The results show that classification accuracy is lower in Gornja Radgona, which can be due to high diversity and detailed land use/cover in this area and thus more difficult separation between classes while classifying.

While using the described procedure we ran into some issues that required extra steps to obtain better final results. As already mentioned, these issues were related to small shadow patches, great areas of shadow in the mountainous are, and to wrong delineation of the segments in the segmentation stage. In the next section solutions to the problems are proposed.

Shadows

We were dealing with two types of shadows, small patches of shadows produced by high objects and bigger areas of shadows in the subalpine area that are the consequence of a elevated terrain. Each shadow issue we tested in separate study areas, although small patches for example can be found on both images.

After obtaining first classification image of total land use/cover in the Kobarid study area we found out that the shadowed conditions of the aerial photographs hampered good classification results. The central part of the area with the city of Kobarid is situated in the Soča valley, but there is a steep terrain in the vicinity – east from the city mountain Krn raises to 2244 meters above sea level (Kobarid lies on 235 meters above sea level). As a result, more than 3% of the image is obscured by shadow. Hence, shading in this area is the consequence of considerable differences in altitude over relatively short distances and high zenith angles of the Sun during the acquisition of an image. Shadows on images in general represent a major problem that can be on middle resolution imagery eliminated by means of topographical normalization, but since we used HR data we approached this problem differently. While classifying the Kobarid area a new "shadow" class (see Figure 5) was added to the existing classes.
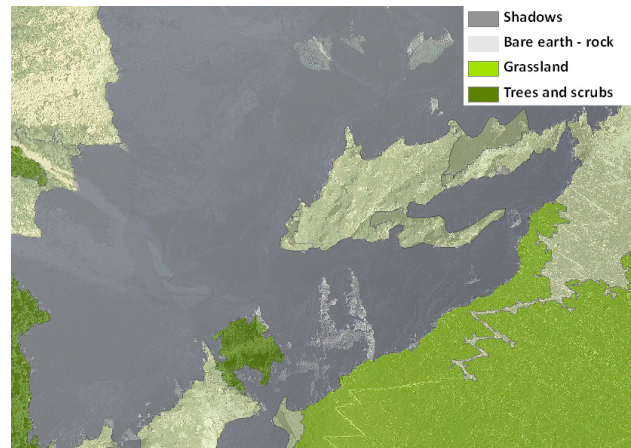

Figure 5: Delineated shadow illustrated on a subset of the aerial image.

This class of shadows was later extracted from the rest of the classification results and masked out separately on a combined image. The procedure of segmentation and classification was repeated, but this time only on the masked shadowed image. Three classes were presented in the shady areas – grassland, trees and scrubs and bare earth – rock. Satisfying results were later manually corrected and added to the whole classified area. The described procedure was carried out in order to avoid misclassified segments within the same class due to different spectral values in the shadowed area, or so that deviations values of the same class would not spoil the total accuracy of the classification.

Overall accuracy of the classification for Kobarid is very good (91.3 %), given the fact that vector results were not manually corrected in the process of post-classification. It can therefore be stated that this procedure solved the problem of shading effect of steep terrain very well.

The Gornja Radgona area is characterized a fragmented landscape with patches of crop fields, grassland, vineyards, sparsely urbanized areas and forests. Small shadow patches appear on the image in combination with high objects – usually when close to high buildings and arboreal vegetation. During visual examination of the results these small areas of shadows can be seen as objects classified erroneous throughout the whole image. The question was either to select these small patches of shadows as part of one geo-object during the training examples procedure or select them separately. The problem was tackled in a different way for each class where these shadowed patches were present.

Since some of these features were merged with predominant classes in the phase of post-classification considering minimum mapping unit (areas smaller than 10 m² for urban land and 5000 m² for water), this type of shadows, as a rule, did not contribute to the general loss of classification accuracy.

First, Shadow Index (SI) was calculated for the entire image, but it did not bring any substantial improvements, so it was not considered in further analysis. Obvious errors of shadow image-objects were therefore manually corrected in the post-classification stage.

The remaining problem was posed by segments of the shadows of trees near water (the Mura river), on the edge of a forest complex (Figure 6).
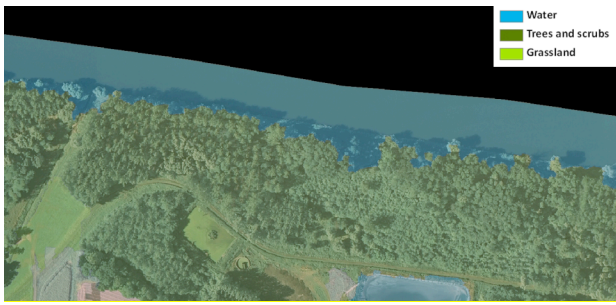
Figure 6: Misclassified segments by the Mura river.

There, segments were misclassified as class "water" instead of class "trees and scrubs" and were manually corrected where obviously inconvenient.

Small patches of shadows in urban area that are usually the consequence of higher buildings were considered as a part of either class "buildings" or "roads" when training classes, since they present mostly small areas on the image. These areas were mostly merged to representative classes when using MMU (Figure 7). It can be assumed that lower classification accuracies of the two mentioned classes in both study areas are the consequence of these small shadowed areas.

Figure 7: Example of classified urban area, where MMU was already considered.

Shadows can also play an important role in object based classification. Good spatial resolution enables classification using texture patterns. For example, frequently arboreal vegetation has a higher number of shadow segments between the leaves, which allows more texture when classifying. Good output results were also obtained in the case of vineyards. Small patches of shadows create good contrast in the combination with fruiting shoots in the parallel line pattern, since vineyard patterns are usually periodical and oriented.

Delineation

The non-matching polygons were first found visually while generally segmenting image into selected classes. The problem of wrong delineation occurs more frequently if one informational class in general does not have linear shape while bordering spectrally similar classes.

To minimize this problem we first computed the separability of selected class pairs, where each class was statistically compared with all other classes. The computation used the Jeffries–Matusita algorithm (ITT, 2009), which measures values in a range from 0 to 2.0 – normally, values greater than 1.9 indicate good separability, whereas pairs with values less than 1 technically represent the same class regarding their spectral properties.

We examined all pairs of selected classes and exposed those with lower separability values (values under 1.5). In both study areas these are the combinations of the following classes: "green crops" – "grassland" (because of their similar vegetation structure), "buildings" – "roads" and "young vineyard" in comparison with "grassland" (Figure 8).

When segmenting the image we considered these separability values and adapted segmentation parameters to spectrally similar classes. This means that our selection of parameters based on the visual perception when delineating between spectrally similar classes, although the effect of segmentation on uniformity is different for each class, and that some other classes were oversegmented. In order to obtain less frequent errors or errors that are easier to fix, some degree of oversegmentation is even desirable (Castilla and Hay, 2008).

Figure 8: An example of wrong delineation of land cover/use.

Forster et al. (2008) stated that smaller scale parameters tend to define more fragmented areas of good and excellent quality, while with a higher combination of scale parameter larger and coherent areas of good and medium quality will occur.

After conducting series of segmentations we obtained optimal parameters for delineating complex and heterogeneous land cover/land use representation (Table 2), although it was impossible to delineate all geo-objects on the image. A certain level of generalization is required for a successful application of the algorithm tailored to a specific scale (Förster et al., 2008).

3. CONCLUSIONS

This paper has demonstrated the problems faced when classifying land use/cover in two study areas in Slovenia. We have demonstrated how to eliminate problems, such as misinterpretation of shadows and shape when using high resolution remote sensing data

In the presented work suitable segmentation parameters for satisfying classification of all the selected classes were used. We have shown that the optimum parameters that can separate relevant information from the image can be identified, using the knowledge of the user and separability information between selected classes.

When dealing with shadows we solved the problem of big shadow areas in Kobarid region by masking these regions out and classifying them separately. The results were later merged with the rest of classification results. Good overall classification accuracy in this region (91.3%) shows that classifying shadows separately has proved to be a good method selection.

Since shadow index calculations did not produce any concrete results, the issues of small shadows were solved partly manually and partly by considering them as part of a class when selecting training examples. Small patches of shadows were therefore either merged to a prevailing neighbouring class or reclassified and assigned to a specific class.

A further improvement of this study can be obtained by a careful analysis of smaller shadows of higher objects and integration of other additional data (such as laser scanning data). Lidar can be used to minimize negative effects of shadowing and consequently improve classification results, since the technology offers height information and can additionally distinguish patches of the same material covered objects.

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5. ACKNOWLEDGEMENTS