A Comparative Analysis of Pixel-Based and Object-Based Approaches Using Multitemporal PlanetScope Imagery for Land Cover Classification

Dino Dobrinić[1,], Mario Miler[1], Damir Medak[1]*

[1] University of Zagreb Faculty of Geodesy, Chair of Geoinformatics, Zagreb, Croatia, dino.dobrinic@geof.unizg.hr; mario.miler@geof.unizg.hr; damir.medak@geof.unizg.hr

* corresponding author

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Abstract: Remote sensing plays a crucial role in monitoring and managing land cover change and provides valuable insights for various applications, including environmental monitoring, urban planning, and natural resource management. In recent years, advances in sensor technology have led to the availability of high-resolution satellite imagery, enabling fine analysis of land cover dynamics. The study uses a multitemporal approach, where PlanetScope imagery are acquired at different points in time to capture temporal variations in land cover characteristics. The eight spectral bands provide improved ways to distinguish between different land cover types, including vegetation, water bodies, urban areas, and agricultural fields. Two classification approaches are evaluated: pixel-based (PB) classification, which assigns a land cover class to each individual pixel based on its spectral characteristics, and object-based (OB) classification, which groups neighbouring pixels into objects or segments and assigns a class label to each object based on its spectral, spatial, and contextual attributes. The OB approach performed better than the PB approach with an overall accuracy of 85.43%, compared to 81.90%, respectively. Also, 'salt-and-pepper effect' was significantly reduced using the OB approach. The study also investigates the potential advantages and limitations of each approach in capturing subtle land cover changes, spatial heterogeneity, and spectral variability.

Keywords: land cover classification; OBIA; pixel-based; Random Forest; segmentation.

1 Introduction

In recent decades, the increasing availability of remote sensing (RS) data, characterized by improved spectral, spatial, and temporal resolution, has been increasingly exploited for the detection and classification of different land use/land cover (LULC) types (Georganos et al. 2018). However, accurate mapping of land cover classes remains a challenge due to the high spectral variation within a class and spectral similarities between different classes (Dobrinić et al. 2021). These challenges cannot be effectively addressed with conventional approaches that rely solely on spectral information for image classification. Spectral heterogeneity within certain land cover types often leads to misclassification of pixels, resulting in a 'salt-and-pepper effect' (Hirayama et al. 2018).

In recent years, Object-Based Image Analysis (OBIA) has established itself as an efficient method for classifying high-resolution satellite imagery (Blaschke 2010). Object-Based Image Analysis (OBIA) methods have been developed to effectively classify satellite imagery with medium to high spatial resolution. These methods present a compelling alternative to traditional pixel-based (PB) approaches. Rather than examining individual pixels, OBIA aggregates pixels into objects or segments using homogeneity criteria, such as spectral or spatial attributes. This approach provides additional geographic and geometric features associated with the objects, including shape, length, neighbourhood, and topology. Therefore, much of the research has focused on comparing pixel- and object-based classifications in heterogeneous landscapes using different machine learning algorithms (Tassi et al. 2021, Qu et al. 2021). Both papers compared PB and OBIA approaches for LULC classification and proved that classification results were improved when applying object-based classification models. Furthermore, additional features were used in these studies to improve classification accuracy, such as spectral indices, topographic features and/or texture variables.

Previous research improved classification accuracy using low-resolution satellite imagery (e.g. Landsat-8 with a spatial resolution of 30 meters). Therefore, the aim of this research is (1) to use the multi-temporal, high-resolution PlanetScope product with a spatial resolution of 3 meters and eight spectral bands for land cover (LC) classification and (2) to compare the accuracies of pixel-based (PB) and object-based (OB) classification methods in delineating land cover types.

2 Materials and methodology

2.1 Research area

The city of Varaždin as an urban settlement and its surrounding areas (e.g. forest, urban green areas, arable land) were selected for land cover classification. Varaždin has a warm-summer, humid continental climate (Dfb) bordering on a maritime climate (Cfb), with an average annual temperature of 10°C and an average annual precipitation of 843.1 mm. For this study, an area of approx. 600 km2 was divided into the following land cover classes: Arable land, forest, water, cultivated soil, bare soil, grassland and orchard (Dobrinić et al. 2021).

2.2 Data

This study used commercial PlanetScope (PS) data for multitemporal (MT) land cover classification. Since 2016, Planet Inc. has provided four-band multispectral imagery (i.e., blue, green, red, and near–infrared - NIR), and since

2019, the SuperDove (PSB.SD) satellite constellation has provided 3-meter multispectral image resolution with eight spectral bands (Table 1). Therefore, three PSB.SD images were selected for LC classification, with 0% cloud cover and as a Level 3A product (Gašparović et al. 2023).

Table 1. Overview of the PSB.SD images used in this research.

Parameter	Value			
Bands	Coastal Blue (B1)	Blue (B2)	Green I (B3)	Green (B4)
	Yellow (B5)	Red (B6)	Red-Edge (B7)	Near-Infrared (B8)
Resolution	3 m			
Date	20/06/2023	20/07/2023	21/08/2023	

2.2.1 *Vegetation Indices*

As mentioned in section 2.2, PSB.SD offers four additional spectral bands compared to the original PS data, which leads to a better differentiation of the different LC classes. Furthermore, a wider range of spectral indices (e.g. vegetation, soil, urban) can be derived from the PSB.SD images, providing a deeper insight into the environmental dynamics. Therefore, NDVI (normalized difference vegetation index), NDWI (normalized difference water index), EVI (enhanced vegetation index), SAVI (soil adjusted vegetation index), and GRVI (green-red vegetation index) were considered in this study. For EVI and SAVI, the L-factor was set to 0.5.

2.3 Land Cover Classification

2.3.1 *Pixel-based*

Pixel-based classification is often used in remote sensing, e.g. in the LC classification of satellite images, where each pixel of the image is assigned a class label. Each pixel is classified independently without considering its spatial context, which can be problematic in complex landscapes. Compared to object-based classification, it is easier to implement and less computationally expensive. In addition, it often relies on spectral indices or statistical methods for classification.

2.3.2 *Object-based*

In object-based image analysis (OBIA), classification is based on pixel groups that take into account both the spectral and spatial properties of the image objects. Therefore, OBIA is well suited for LC classification in heterogeneous landscapes with spatially coherent features. In this study, the image was segmented before classification using the multi-resolution segmentation (MRS) algorithm, which is known as a bottom-up method for merging regions (Liu et al. 2018). The selection of optimal segmentation parameters, i.e., scale, shape, and compactness, is often based on trial and error (Hay and Castilla 2008), and the parameters were set to 45, 0.3, and 0.5, respectively.

2.4 Accuracy Assessment

The results of the pixel- and object-based classifications were evaluated using a standard confusion matrix to calculate the overall accuracy (OA) and the kappa coefficient (Olofsson et al. 2014). In addition, producer and user accuracy was determined to assess omission and commission errors for each class (Olofsson et al. 2014). Furthermore, stratified random sampling was performed for LC classification (Table 2). A total of 662 samples were randomly divided into a training set (70%) and a test set (30%).

Table 2. The number of used pixels for PB and number of image objects for OB classification.

Class	Pixel-based	Object-based
Cropland	61205	100
Forest	67204	39
Water	207246	40
Built-up	6233	248
Bare soil	68736	40
Grassland	55957	195

3 Results and discussion

The results of LC classification using pixel-based and object-based approaches and multitemporal PS images are shown here. Although the focus of this study was on the comparison between the PB and OB, it should be noted that Random Forest (Breiman 2001) was used as the machine learning method. The OB approach performed better than the PB approach with an OA of 85.43%, compared to 81.90% (Table 3). Similar performance was achieved in the study by Qu et al. (2021), where the OB approach outperformed the PB approach by 1.81% and showed better performance in identifying smaller objects, resulting in a reduction of the salt-and-pepper effect. Similar performance (i.e. OB outperformed the PB approach) was also shown in the study by Cui et al. (2022), where PS images were used with the RF algorithm and an OA of 93.87% was achieved.

In addition, Table 3 shows a detailed insight into the ability to discriminate between land cover classes by the accuracy of the user (UA) and producer (PA). The highest accuracy was obtained for the water class (large homogeneous area) for both approaches, while the OB approach proved its superiority for small objects assigned to the built-up class. Lower accuracy values were obtained for the vegetation LC classes (i.e. cropland, grassland) in heterogeneous landscapes. There are two possible reasons for this: (1) lower quality of vegetation patterns used from the national ARKOD Land Parcel Identification System (LPIS), and (2) for the OB approach, the segmentation parameters, i.e. scale, shape and compactness, need to be fine-tuned for the delineation of agricultural fields. Aguilar et al. (2016) tested different combinations of shape and compactness values for extracting greenhouses from WorldView-2 images to determine the optimal setting of segmentation parameters for multi-resolution parameters.

As mentioned in the Introduction, the traditional PB classification method can lead to a "salt and pepper" effect, while the OB approach reduces this problem by considering the neighborhood information of a given pixel (Luo et al. 2021).

Table 3. Overall and per-class accuracy (%) for PB and OB approach.

Class / accuracy	**Pixel-based**		**Object-based**	
	PA	UA	PA	UA
Cropland	66.67	72.73	63.33	70.37
Forest	100.00	71.43	100.00	85.71
Water	100.00	100.00	100.00	100.00
Built-up	90.00	87.10	95.95	91.03
Bare soil	78.95	76.92	75.00	90.00
Grassland	78.95	84.37	79.66	81.03
OA	81.90		85.43	
Kappa	0.76		0.80	

Figure 1 shows a comparison of LC classification with the PB approach (left side) and the OB approach (right side). Due to the limited scope of the paper, only a subset of the study area is shown, but the improvements in LC classification with the OB approach can be seen in the central part of Figure 1 for the "Built-up" class and for the vegetation classes (i.e. forest and grassland) in the northern part of Figure 1. The delineation of the arable land class is also better recognizable with the OB approach.

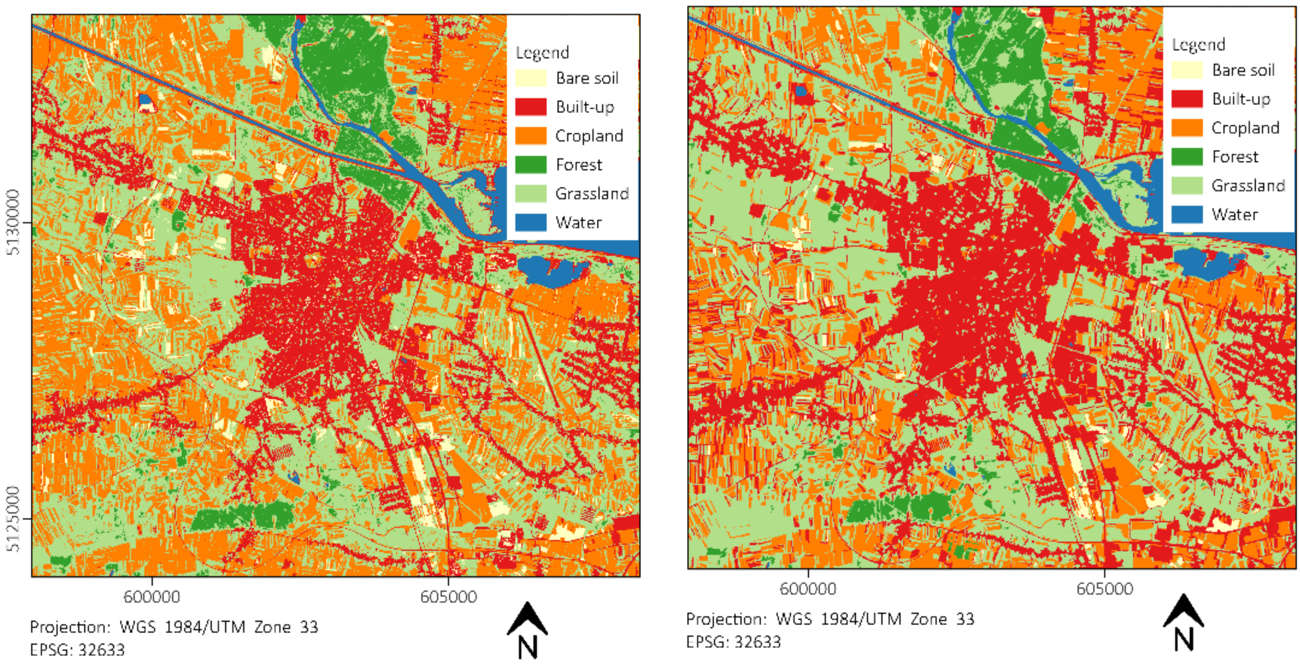

Figure 1. LC classification with the PB (left) and the OB (right) approach using the RF algorithm.

Although the OB approach outperformed the PB approach in LC classification using MT Planetscope images, some limitations of the study need to be mentioned. First, the samples were collected via the national ARKOD LPIS database and manually. Since the overall accuracy of LC classification depends on the quality and semantic distribution of the reference dataset, its refinement needs to be ensured e.g. by the CORINE or LUCAS LC database (Dobrinić et al. 2021). In addition, further research should focus on a specific task (e.g. classification of urban areas, vegetation mapping, wetland monitoring, etc.), as the segmentation parameters are highly dependent on the classification task and their determination can directly influence the subsequent classification (Ma et al. 2017).

4 Conclusions

The aim of this study was to use multi-temporal, high-resolution PlanetScope imagery and compare the performance of pixel-based (PB) and object-based (OB) approaches to land cover classification. The OB method performed better than PB with an overall accuracy (OA) of 85.43% compared to 81.90%. Possible factors contributing to lower accuracy per class include the quality of vegetation samples from the national Land Parcel Identification System (LPIS) and the need for finer adjustment of segmentation parameters for agricultural field delineation in the OB approach.

Overall, this comparative analysis highlights the potential of the OB approach using multitemporal PlanetScope imagery for land cover classification while highlighting areas for further refinement and optimization, especially in the context of vegetation classification in heterogeneous landscapes. Further research should focus on more advanced deep learning techniques (e.g., convolutional neural networks), which can exploit relations between pixels and objects on the satellite imagery.

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