URBAN VEGETATION DETECTION BASED ON THE LAND-COVER CLASSIFICATION OF PLANETSCOPE, RAPIDEYE AND WORLDVIEW-2 SATELLITE IMAGERY

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ABSTRACT

One of the problems that are encountered today is the migration from rural to urban areas. Cities are becoming overpopulated and consequently overbuilt. Due to the high demand for new residential and commercial buildings, in the last few decades, green zones such as parks are often becoming built. In the cities, there is increasingly less room left to nature. Urban vegetation has a large impact on the quality of life in cities.

The aim of this research is the detection of urban vegetation by three independent multispectral (MS), and high spatial resolution satellite imagery. Satellite imagery with various spatial resolution and spectral characteristics are used in this research. The study area is the capital city of Croatia, Zagreb. For this research MS imagery from PlanetScope (PS), Rapideye (RE) and WorldView-2 (WV2) satellites were obtained within project "Geospatial Monitoring of green infrastructure by means of terrestrial, airborne and satellite imagery" (GEMINI). PS 3.7-m spatial resolution imagery has 4 bands (blue, green, red and near-infrared), RE 5-m spatial resolution imagery has 5 bands (blue, green, red, red edge and near-infrared) and WV2 2-m spatial resolution imagery has 8 bands (coastal, blue, green, yellow, red, red edge, near-Infrared 1 and near-infrared 2). Above mentioned satellite imagery with different spatial resolution and spectral characteristics were used to obtain three independent land-cover classifications of the city of Zagreb. Based on the land-cover classification entire study area was divided into 5 classes (water, bare soil, built-up, forest and low vegetation). Supervised classification was made with a random forest (RF) classifier based on manually collected training polygons. Accuracy assessment of the different resolution land-cover classifications was calculated based on the reference polygons. The main goal of this research is the accuracy comparison of the land-cover classifications conducted on three different satellite imagery sources. According to expectations highest overall accuracy and user's accuracies for each class has WV2 satellite imagery, then PS, and lowest accuracy has RE satellite imagery. This is important for the further research on project GEMINI especially for detection and monitoring of urban vegetation as one of the most important factors of life quality in cities.

Keywords: land-cover classification, satellite imagery, urban vegetation detection, remote sensing, accuracy assessment.

INTRODUCTION

Satellite imagery acquired using remote sensing (RS) provide a big amount of a spatial data with a daily revisit time which can be used in many scientific disciplines. One of the problems that are encountered today is the migration from rural to urban areas. Cities are becoming overpopulated and consequently overbuilt. The consequence of that is in a decrease of the green zones in the cities, such as parks, community gardens, playgrounds. Satellite imagery classification can easily detect insight in the land-cover structure of the cities. Classification of the satellite imagery represents the connection between remote sensing and geographic information systems (GIS). A raster image can be interpreted as a quantitative layer which can be used for detecting land-cover classes on the Earth's surface [1].

Satellite imagery classification methods can be distinguished into two categories: unsupervised and supervised methods. Unsupervised classification technique uses clustering mechanisms to group satellite image pixels unto unlabeled classes/clusters [2]. Most common unsupervised satellite image classification is ISODATA [3], Support Vector Machine (SVM) and K-Means [4]. Supervised classification requires a training set by an operator. Accuracy highly depends on the polygons taken for training. Most common classification techniques used with RS image data are Maximum Likelihood, Minimum Distance, Artificial Neural Network (ANN), Binary Decision Tree (BDT) [2]. Popular machine learning algorithm for image classification that is a collection of decision trees is random forest [5], [6].

In the past, most land-cover classifications have been created using a pixel-based analysis of remotely sensed imagery. These procedures analyse the spectral properties of every pixel within the area of interest, without considering the spatial or contextual information related to the pixel of interest [7]. Due to the "salt and pepper" effect [8], that decreases the accuracy of the classification when pixel-based methods are applied to high-resolution images, object-based image analysis (OBIA) has been developed [7]. OBIA analyze both the spectral and spatial properties of pixels and predicates segmentation of the image data. The main advantage of segments is the more natural representation of the real-world objects, which promises to be more accurate than traditional pixel-based methods [9].

Main goal of this research is the detection of urban vegetation by three independent multispectral (MS), and high spatial resolution satellite imagery. This is important for the further research on Geospatial monitoring of green infrastructure by means of terrestrial, airborne and satellite imagery (GEMINI) project, especially for detection and monitoring of urban vegetation as one of the most important factors of life quality in cities.

STUDY AREA AND DATA

In this research, land-cover classifications were examined for the study area which is located in Zagreb, the capital city of Croatia. Zagreb has an area of 641 square km, and according to last population census from 2011, the area has 790 017 inhabitants, with a positive yearly increase in the number of inhabitants. Due to the high demand for new residential and commercial buildings, in the last few decades, green zones such as parks are often becoming built. For this research central urban, eastern and southern lowland parts of the city were taken into consideration with an area extent of 130 square km (11.6 km x 11.2 km). The research area is surrounded by a Medvednica mountain on the north and river Sava on the south (Figure 1).

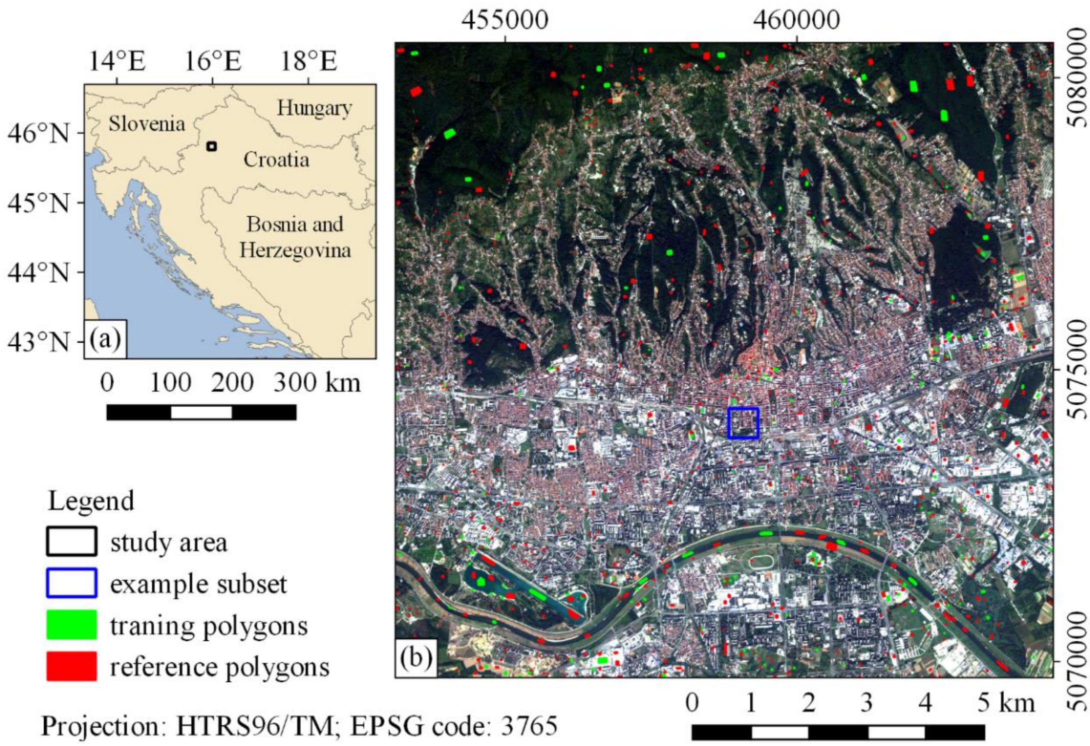

Figure 1. (a) Study area location; (b) distribution of the training and reference polygons, as well as, example subset location (background: satellite image RapidEye 'true colour' composite (3–2–1), sensing date: 12/09/2016).

For this research, RapidEye (RE), PlanetScope (PS) and WorldView-2 (WV2) satellite imagery with different spectral resolutions (Figure 2) were acquired. RE 5-band MS analytic data product – Ortho Tile with a spatial resolution of 5 m and for the date 12/09/2016 was used in this research. PS 4-band MS analytic data product – Basic Scene with a spatial resolution of 3.7 m and for the date 09/09/2016 was used for this research. WV2 OrthoReady Standard (ORS2A) 8-band MS image with a spatial resolution of 2 m, and for the date, 08/08/2013 was used for this research. PS and ORS2A imagery are suitable for the orthorectification, to improve the horizontal accuracy. Digital elevation model (DEM) used for orthorectification of the PS and WV2 ORS2A is the Shuttle Radar Topography Mission (SRTM) with a spatial resolution of one arc-second (~30 m).

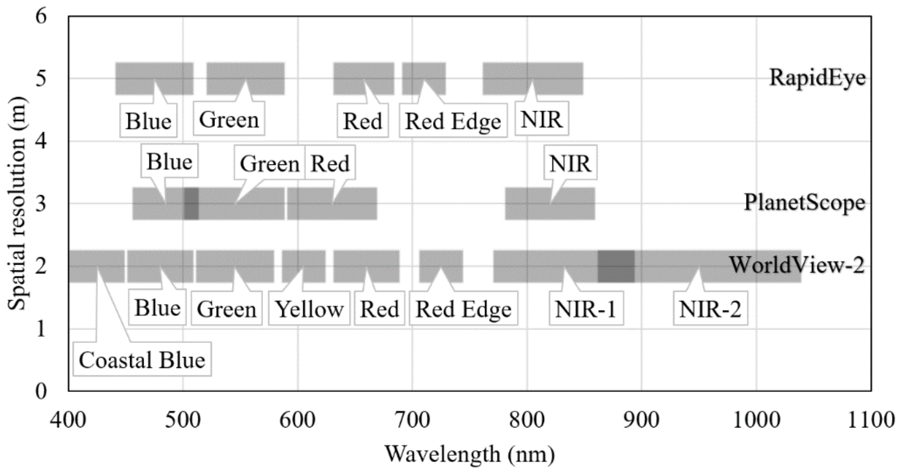

Figure 2. Overview of the RapidEye, PlanetScope and WorldView-2 spectral bands.

METHODS

In this research supervised classification was made with a random forest (RF) classifier. The RF classifier is a combination of tree predictors where each tree depends on the values of a random vector sampled independently from the input vector, and with the same distribution for all trees in the forest [10]. This classifier has become popular in the remote sensing community due to the accuracy of its classifications and for the ability to learn the characteristics of target classes from training polygons [11].

Training polygons for the classification were selected, on the WV2 imagery, randomly and equally for each class. For this research land-cover was divided into five classes: water, bare soil, built-up, forest and low vegetation (Table 1).

Table 1. Description of the classes.

ID	Class	Description
1	Water	Water bodies – lakes, rivers
2	Bare soil	Surfaces without vegetation – soil, rocks
3	Built-up	Human-made constructions – buildings, roads
4	Forest	Wood vegetation – coniferous/non-coniferous forests, shrubs
5	Low vegetation	Annual plants – natural grass, crops, pastures

Overall 200 training polygons (Figure 1) were manually collected, which makes a part of a 0.20% from the overall area of the study data. According to [12], sizes of the training polygons should represent 0.25% of the total study area. Pixel-based classifiers develop a signature combining the spectra of training-set pixels for a given feature. The resulting signature contains the contributions of all materials present in the training pixels [13]. Classification with RF classifier was conducted with a maximum tree depth of 10 and a minimum sample count of 2, to reduce memory consumption.

Reference polygons (Figure 1) for land-cover classification accuracy assessment were chosen without overlapping with training polygons. Overall 600 polygons were collected as reference polygons, with a share of a 0.25% from the overall area of the study area. The error or a confusion matrix is one of the most widely used in accuracy assessment [14]. Confusion matrix shows class types determined from reference source in columns, and class types determined from the classified map in rows. Diagonals represent polygons classified correctly according to reference data, while off-diagonals were misclassified. Furthermore, overall accuracy is defined as a sum of the diagonal elements divided by a total number of elements. Besides the overall accuracy, within the confusion matrix, omission and commission error can be analysed. Omission error occurs when polygons of the reference data are allocated in other classes, while commission error occurs when polygons from other classes are allocated in the reference data.

The kappa coefficient is a measure of overall statistical agreement of an error matrix, which takes non-diagonal elements into account. Kappa analysis is recognised as a powerful method for comparing the differences between various error matrices [14]. It is considered that kappa coefficient values between 0.41 and 0.60 represent moderate classification accuracy, values between 0.61 and 0.80 high accuracy, and values greater than 0.80 very high classification accuracy [15]. There is also a distinction between producer's accuracy and user's accuracy. Former represents accuracy regarding reference data, and latter represents reliability regarding classified data. Above described methods were made in open source programs Quantum GIS (QGIS, version 2.18.4), GRASS GIS (version 7.2.0) and SAGA GIS (version 6.2.0).

RESULTS

As mentioned in the previous section, after the image classification based on the 200 training polygons, accuracy assessment was made on 600 reference polygons. In Table 2 are shown user's accuracy (UA), producer's accuracy (PA) for each class and overall accuracy (OA) of the classification. Highest overall accuracy has classification made on the WV2 imagery, then PS and RE imagery. From the values of user's accuracy for all three imagery classes, water and forest have the highest accuracy of the classification, and low vegetation has lowest accuracy.

Table 2. Classification accuracies (%) based on the RE, PS and WV2 satellite imagery.

Class ID / Source	1		2		3		4		5		OA
	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	
RE	98.9	89.6	49.6	37.3	81.6	84.5	94.2	93.4	33.5	60.2	83.8
PS	93.6	89.8	56.9	57.1	84.3	84.7	96.4	92.6	38.6	57.1	85.2
WV2	99.9	89.9	72.3	86.6	86.3	88.9	98.7	92.6	54.7	81.4	90.1

From the confusion matrix, statistics measure such as omission (O) and commission (C) error, kappa coefficient (Kappa), can be derived (Table 3). Reason for high omission errors are misclassified pixels from low vegetation to forest, and for pixels in class bare soil that were misclassified as built-up. Additional accuracy assessment can be made with the kappa coefficient. This statistic element is a measure of how well a classification map and the associated reference data agree with each other. According to [15], WV2 and PS have very high classification accuracy, and RE has high accuracy.

Table 3. Commission, omission (%) and a kappa coefficient of the classification.

Class ID / Source	1		2		3		4		5		Kappa
	O	C	O	C	O	C	O	C	O	C	
RE	10.4	1.1	63	50.4	15.5	6.6	6.6	5.8	39.8	66.5	0.77
PS	10.2	6.4	43	43.1	15.3	15.7	7.4	3.6	42.9	61.4	0.80
WV2	10.1	0.1	13	27.7	11.1	13.7	7.4	1.3	18.6	45.3	0.86

Since the acquired satellite imagery covers a large part of Medvednica mountain on the north, the forest has the biggest share in the land-cover classification, and it is in between 35% – 38%, while water has the smallest share of 2% – 4% (Figure 3).

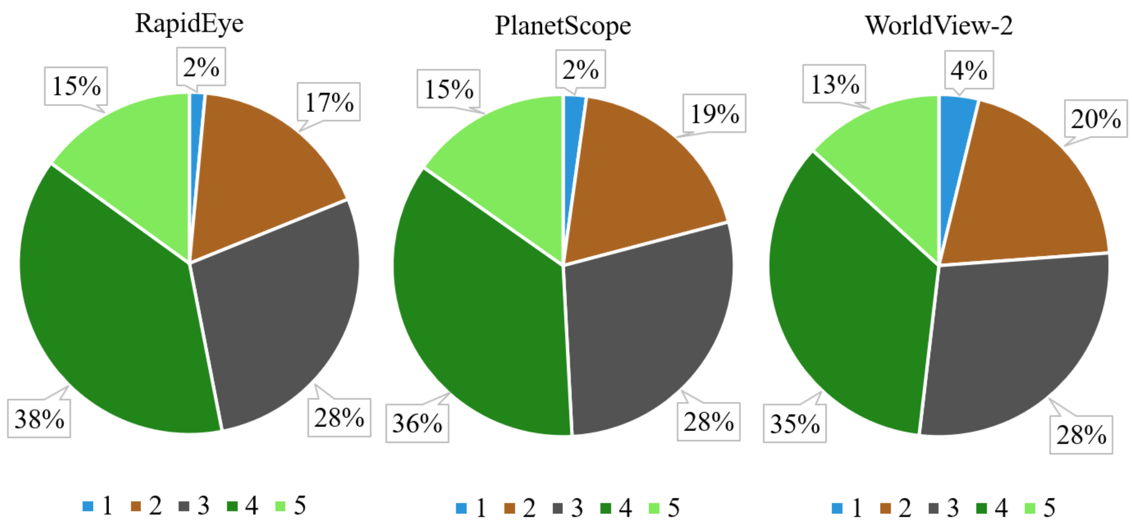

Figure 3. The share of the land-cover classes for RE, PS and WV2 classification.

Figure 4 shows a 500 m x 500 m example subset of the central part of Zagreb, which shows the Botanical garden and other urban vegetation, roads and built-up area. PS and RE satellite imagery with a lower spatial resolution than WV2 had problems with shadows of the tall buildings during classification. They were misclassified as water.

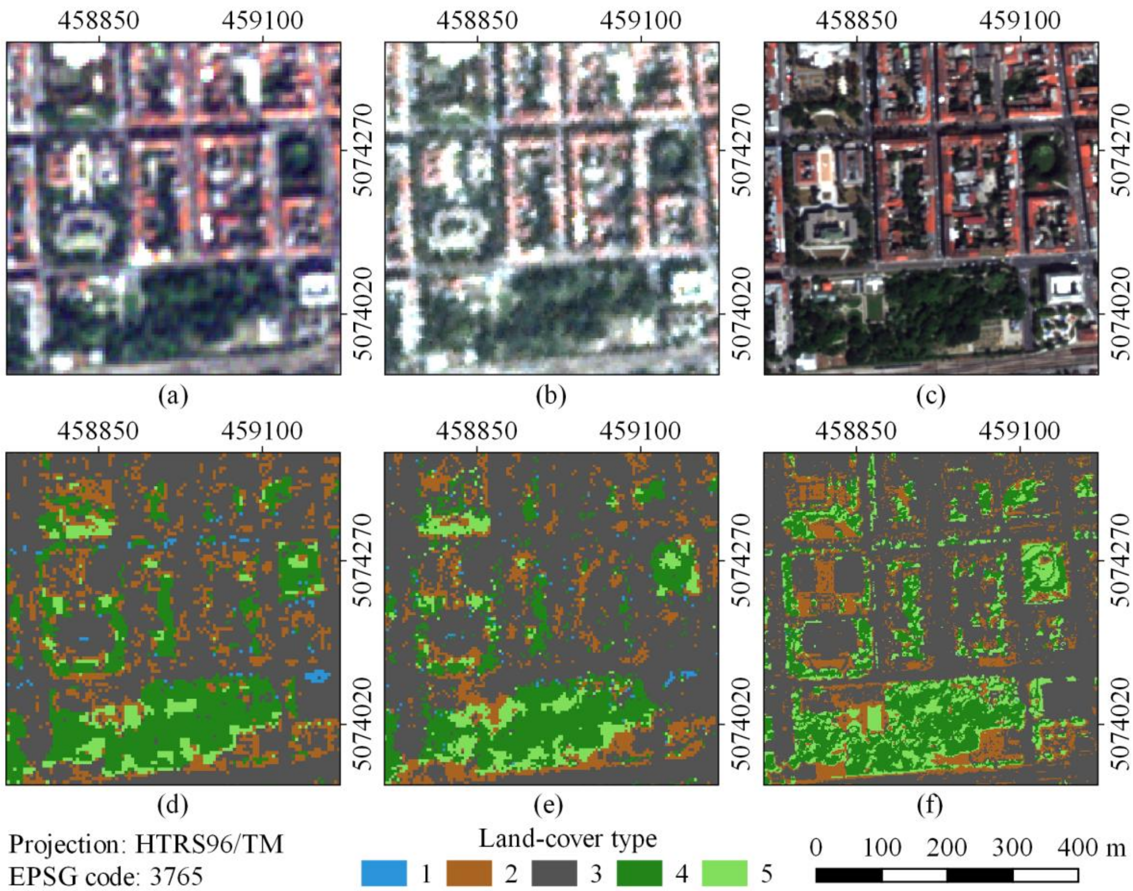

Figure 4. Comparative visual analysis on the example subset of the RF classification results (d), (e) and (f) based on the (a) RE, (b) PS and (c) WV2 satellite imagery.

CONCLUSION

In this research land-cover classification of the RE, PS and WV2 satellite imagery was made. RF classifier was used for classification, and land-cover was divided into five classes: water, bare soil, built-up, forest and low vegetation. Image classification was made based on 200 training polygons, and accuracy assessment was made and compared on 600 reference polygons.

As shown in the previous section, as expected highest overall accuracy and user's accuracies for each class has WV2 satellite imagery, then PS and lowest accuracy has RE satellite imagery. If we compare user's accuracy which represents reliability regarding classified data, WV2 has almost 50% higher accuracy than PS and RE imagery for bare soil and low vegetation class. Bare soil and low vegetation are often misclassified as built-up and forest, respectively. Furthermore, if we compare kappa coefficient which is a measure of how well a classification map and the associated reference data agree with each other, WV2 and PS have very high classification accuracy, and RE has high accuracy. The class forest has a biggest share in overall area, and for RE, PS and WV2 imagery user's accuracy is 94.2%, 96.4% and 98.7%, respectively. This is important for the further research on project GEMINI especially for detection and monitoring of urban vegetation as one of the most important factors of life quality in cities.

In this research comparison of satellite imagery classification that is acquired from different sensors and has a different spatial resolution was made. Free and open source programs were used (SAGA, QGIS, GRASS GIS) along with imagery available for scientific research. A further investigation of different methods for supervised classification of satellite imagery or object-based image analysis (OBIA) would be interesting for using classification results in detection of urban vegetation.

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