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Methods of Land Cover Classification Using Worldview-3 Satellite Images in Land Management

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Abstract: Modern geoinformation technologies, such as remote sensing satellite missions and classification methods, are becoming increasingly prominent in land cover classification. Due to the emergence of high spatial resolution missions with improved temporal and spectral resolutions, such as Worldview-3, this approach enabled new possibilities in land management. To provide an in-depth analysis of such possibilities, this study reviews methods of land cover classification using WorldView-3 satellite imagery. With 29 different spectral channels and a spatial resolution of 1.2 m, Worldview-3 multispectral satellite images represent the most modern currently publicly available commercial multispectral images. The classification of multispectral images is performed to facilitate the identification and recognition of objects in the images. Analyzed classification methods are: supervised (semi-automatic) classification methods, unsupervised (automatic) classification methods, and object-based classification methods. In order to increase the accuracy in land cover studies, it was determined as necessary to develop automatic methods that rely on a combination of controlled and uncontrolled classification methods. This approach enables the automatic determination of samples for conducting supervised classifications of interest for land management.

Keywords: high-resolution imagery; multispectral imagery; OBIA; remote sensing; segmentation; supervised classification

1 INTRODUCTION

Remote sensing is finding increasing application in various scientific fields, including agricultural land management [1]. The non-sustainable management leads to soil degradation and impaired sustainability as the products of human activities in the global ecosystem [2, 3]. It also disregards accidental or intentional release of unwanted chemicals, biological and physical material, or energy into the ecosystem. These products include elements that disrupt the normal functioning of the ecosystem. Global research estimates that 80% of contamination comes from land-based sources [4]. Terrestrial activities and sources of contamination remain major threats to the ecosystem as well [5]. The classic parameters which are affected include temperature, electro-conductivity, pH, and soil organic matter.

However, modern technologies such as remote sensing sensors used to map and monitor contamination (oil, solid waste, soil erosion, algae blooms) and to assess the environmental impact or predict contamination trends are also gaining prominence [6]. With the help of satellite images, the reflectance of various objects in the range of electromagnetic radiation that is not visible to humans became measurable [7]. The importance of satellite images that can be of different spatial, radiometric, spectral and temporal resolutions and therefore applicable for different purposes has been recognized worldwide, including in Croatia [8–10]. Satellite images of higher spatial resolutions, such as Worldview-3, reduce the possibility of overlapping spectral values among neighbouring pixels [11]. Furthermore, higher spatial resolutions represent a great potential for obtaining a large number of more detailed information [12]. Therefore, their use is very important because it is very difficult to directly identify the desired element by visual interpretation.

The aim of this paper is to review modern land cover classification methods using Worldview-3 satellite imagery as a basis for the decision-making in land management. The particular focus was given to the classification process and its potential automation, to improve the widespread availability of such methods in the future.

2 WORLDVIEW-3 (WV-3) MULTISPECTRAL SATELLITE MISSION

Depending on the pre-processing level and applied corrections, WV-3 satellite imagery are available in the following six basic product types: Basic 1B Imagery, Basic 1B Stereo Imagery, Standard 2A Imagery, OrthoReady OR2A Imagery, OrthoReady Stereo OR2A Stereo Imagery and Orthorectified imagery [8]. The display of differences in spectral properties between multispectral images over the same area before and after orthorectification is displayed in Fig. 1.

Figure 1 Worldview-3 image before (A) and after (B) orthorectification

With a total of 29 different spectral channels (8 multispectral channels, 8 SWIR channels, 12 CAVIS channels, and 1 panchromatic channel) and a spatial resolution of 1.2 m, WV-3 multispectral satellite images are the most modern currently publicly available commercial multispectral images [13]. The spectral channels of the multispectral WV-3 satellite mission are shown in Tab. 1.

Table 1 Spectral bands of a multispectral WV-3 satellite mission

Spectral band	Areas of application
Coastal	Coastal research; shadow detection; differentiation of land and water surfaces
Blue	Coastal research; forest classification; differentiation of soil and vegetation; water surfaces
Green	Type of agricultural crops; bathymetry; seagrass detection
Yellow	CO_2 concentration; differentiation of iron ores; sediment analysis
Red	Vegetation classification and analysis; chlorophyll absorption
Red Edge	Health, age, and type of vegetation; seagrass and reefs; separation of land
Near-Infrared 1	Study of biomass; plant stress; material differentiation; separation of water surfaces; soil moisture detection
Near-Infrared 2	Study of biomass; plant stress; material differentiation

Due to the reflection of various objects in the range of electromagnetic radiation that is not visible to humans, it is possible to identify the desired element by visual interpretation [14]. The reflection of electromagnetic waves depends on both chemical and physical soil properties [15]. Water and moisture content produces a low reflection in the visible part of the spectrum while near-infrared (NIR) area there is no reflection due to the absorption of clear water. High reflections in the red and NIR part of the spectrum indicate a high concentration of the substance in water [16].

3 METHODOLOGICAL FRAMEWORK FOR LAND COVER CLASSIFICATION

Classification is based on assigning pixel values to selected, pre-determined spectrally specific classes [17]. The classification of multispectral images is a process, which includes the verification of test samples depending on the classification algorithm used. The classification of multispectral images is carried out to facilitate the identification and recognition of objects in the images. The procedure and choice of classification are very important when calculating a classified raster [17]. The wrong choice of classification method or incorrectly defined training samples can lead to significant errors in the output model [18]. The simplest definition of classification would be to group certain parts of the image into spectral and then information classes afterward based on their similarities [19]. The basic element of a multispectral image and any raster data is a pixel. It is treated as a separate unit containing digital number (DN) values from several spectral bands. The DN number is recorded depending on the radiometric resolution of the satellite image. By comparing pixels with each other, it is possible to determine classes (groups) that are then linked to information categories that are of interest to users. Classes generally represent land cover. Land cover can consist of natural or artificial structures that cover a certain part of the Earth's surface, such as vegetation, water surface, buildings, forests and wetlands [20] (Fig. 2).

Since the images contain information in several parts of the electromagnetic spectrum beyond human visual perception, spectral information represented by pixel values in different spectral ranges is used for classification [21]. The basic problem of image classification is to establish connections between spectral and information classes. The problem is complicated by the fact that within one information class there can be variability so that its pixels belong to different spectral classes. On the other hand, it is possible that pixels that have the same spectral values belong to different information classes.

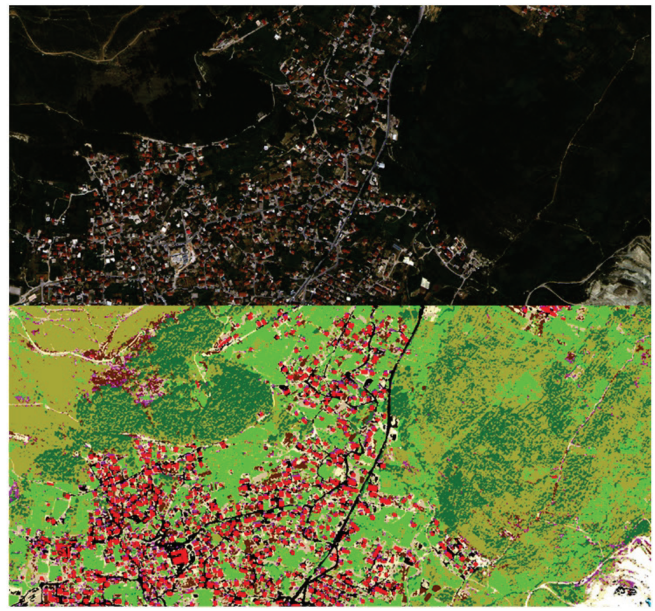

Figure 2 Display of the satellite image and land cover model of the same area

4 CLASSIFICATION METHODS

Classification methods can generally be grouped into supervised (semi-automatic) classification methods, unsupervised (automatic) classification methods, and object-based classification methods [22, 23]. The classification of land cover and land use is based on the different spectral responses of different materials. The fundamental principle of spectral classification is to distinguish between objects using variations in reflectance or emission properties that are dependent on wavelength. However, spectral classification encounter difficulties and lower accuracy in regions where many land cover types have similar reflectance patterns, resulting in a spectral confusion.

4.1 Supervised Classification Methods

The supervised classification method represent the classification of a specific scene/image based on user-defined samples. These are used to define land cover classes, and class determination is done on the spectral characteristics of each sample. The best-known conventional algorithms of supervised classification are maximum-likelihood and minimum distance. In the supervised classification, samples of known identity are taken for the classification of pixels of unknown identity, by the placement of unclassified pixels in one of the information classes [24]. Labeled samples, which are composed of a large number of pixels, sample the spectral characteristics of information categories. It is recommended that the marked areas should contain at least 100 pixels for each class [25]. The advantages of supervised classification are that the operator has control over the selected information categories provided for a particular location. The primary components of the supervised classification are represented in Fig. 3.

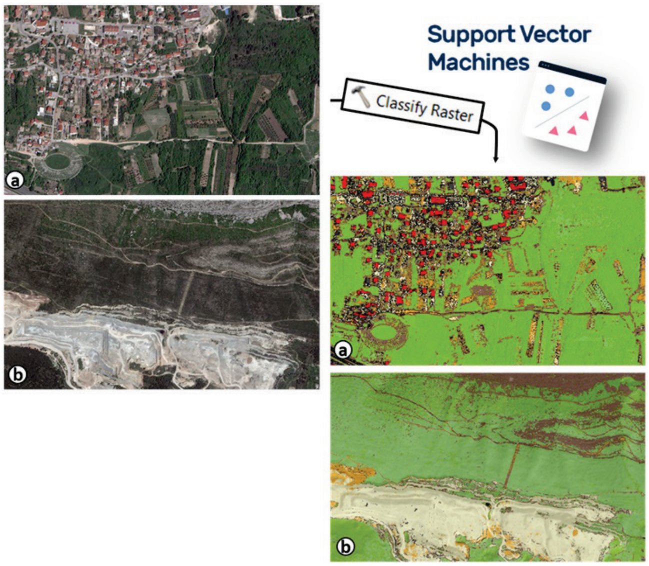

Figure 3 Thematically classified data set with land cover classes for: a) agricultural land in urban areas, b) agricultural land in rural areas

The most notable drawback of supervised classification is that the operator defines the classification structure of the data itself [26]. These classes do not have to match natural classes. Secondly, the samples selected by the operator may be an inaccurate representation of those conditions that take place within the rest of the image. The next disadvantage includes the work itself that the analyst must do to complete the analysis. Selecting data for samples alone can take an extraordinary amount of time. The remaining significant flaw of the supervised classification describes the limitation of man as a classifier. Given that the operator defines the information categories, there is a great possibility that the category that should have been present is omitted because of the operator's false subjective assessment [27].

4.2 Unsupervised Classification Methods

The unsupervised classification method automatically classifies the scene based on the statistical grouping of spectral features and characteristics [17]. It is based on grouping pixels so that their spectral values meet some criterion of homogeneity [28]. For some algorithms, this criterion can be set in advance by specifying the allowable variability of pixel values, while for some algorithms only the desired number of categories is specified. Starting from the given parameters, the classification algorithm finds the natural structure in the data set. The result of classification is a set of spectral classes that then need to be paired with information classes. The user only needs to define the number of classes to be created. Various grouping algorithms are used to determine the statistical data group. Pixels are grouped together depending on their spectral similarity. The computer then analyses each group and categorizes them separately into appropriate classes. If the analyst determines that the image is classified into 10 different classes, the algorithm will create the proposed 10 classes according to the spectral similarity of the pixels. The most well-known algorithms are K-means and ISODATA [29]. Fig. 4 shows an example of noise that occurs when performing an unsupervised classification on a part of a multispectral image.

Figure 4 Noise in the classification result after the unsupervised classification for: 1) predominantly rural areas, 2) predominantly urban areas

The advantages of unsupervised classification are automation, easier work of analysts, reduced space for human error, and no need for a thorough knowledge of the image being processed [30]. In unsupervised classification, most processes are automated and the influence of analysts on the classification process itself is minimized. The shortcomings and limitations of unsupervised classification are mostly due to the reliance on "natural" grouping and the difficulty of categorizing them into information classes according to study focus [31]. The supervised and unsupervised methods are based on the spectral analysis of each pixel in the study area, neglecting the spatial and contextual information of the surrounding pixels. The specific property of pixel-based approaches on high-resolution images is producing a "salt-and-pepper" effect (Fig. 5), which contributes to inaccurate classification.

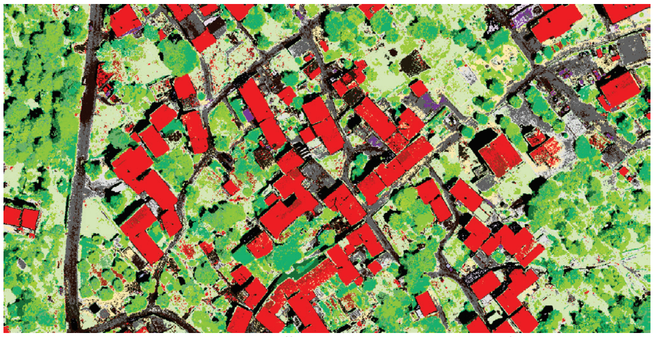

Figure 5 The “salt-and-pepper” effect in the pixel-based classification process

4.3 Object-oriented Classification Methods

In order to eliminate these problems, object-oriented classification procedures have been developed to analyze spatial and spectral properties in a segmentation process. The typical methodology of the object-oriented classification approach is presented in Fig. 6. In general, several classification methods should be evaluated during the study to evaluate the most accurate one, as their effectiveness typically depends on the properties of input data. By integrating these segments in the iterative learning algorithms, the main aim was to achieve more accurate results than pixel-based methods. OBIA is a method that creates objects of different shapes and sizes, while methods based on pixel classification generate square pixels [32].

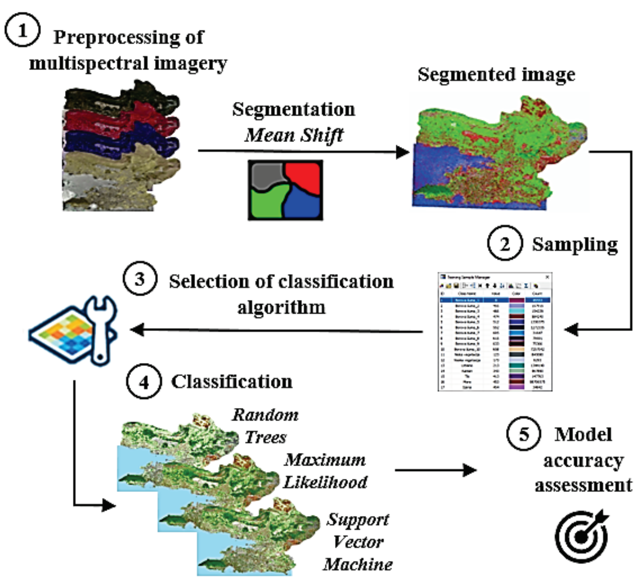

Figure 6 The methodological framework for land cover classification using OBIA

In summary, there are two basic components to OBIA: the first component is based on segmentation and the second is based on classification (Fig. 7). The object-oriented feature extraction process involves a work process that covers three main functional areas: image segmentation, generation of analytical data on segmented parts, and classification [33]. It can be said that OBIA is a process identical to the supervised and unsupervised classification, with a segment or superpixel being classified, instead of individual pixels. Each segment or superpixel is characterized by a specific spatial and spectral set of values that ultimately determine which class it belongs to [34]. Segmentation groups pixels with similar spectral characteristics that are located in close proximity to one segment.

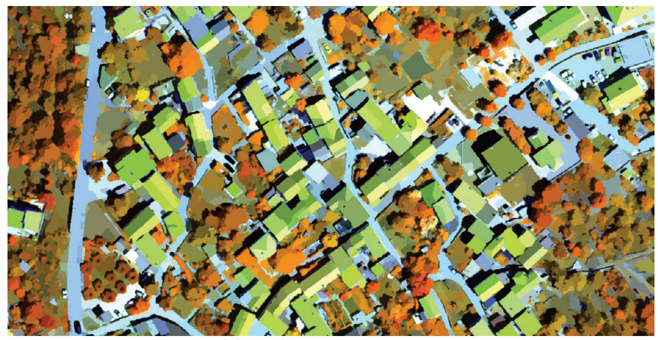

Figure 7 The result of OBIA for land cover, including segmentation and classification

The Mean Shift approach to segmentation uses a moving square matrix when calculating the average value of pixels that can be a part of the particular segment [35]. As the moving grid of squares moves over multispectral images, pixel values are calculated iteratively to check the suitability of each segment. The result is a grouping of pixel images into segments characterized by spectral similarity of reflection. The output of the Mean Shift tool is a 3-channel, 8-bit resolution segmented image. Spectral detail is a parameter that sets the level of importance given to the spectral differences in the multispectral image [30]. In geographic information system (GIS) it varies from 1 to 20. Higher values mean that in the segmentation process great importance is given to spectral differences between pixels. In other words, higher values are used when some features on a multispectral model have similar spectral characteristics, but these should be classified into separate classes. Smaller values create spectral smooth outputs. For example, higher values allow differentiation between different trees, while lower values represent everything as one class. Spatial detail is a parameter that determines the importance of proximity between features in a multispectral model [30]. Valid values in GIS also range from 1 to 20. A higher value is appropriate for a scene where small compact features should be singled out, while lower values create a spatially smooth result. For example, if high-value buildings and roads are set up in an urban area scene, they can be classified as special classes (greater spatial detail). On the other hand, if smaller values of the urban scene are selected in the same scene, it will be classified as a single class with less spatial detail. The minimum segment unit is a parameter expressed in pixels. It merges segments smaller than this size with its most suitable adjacent segment. Band indexes are a parameter related to the selection of one or more bands to be used in segmenting a multispectral image. The bands in which the differences between the features are most noticeable are selected. The size of the objects created by image segmentation depends on the details of the desired land cover model and the input data. After segmentation, there is a classification of isolated objects. They are classified based on object-specific statistical parameters. Finally, taking into account the spatial and spectral characteristics of the multispectral image, it is very important which of the above three classifications is used to obtain the most accurate and time-optimal results [35].

5 CONCLUSIONS

Remote sensing methods and techniques using WorldView-3 satellite imagery allow application in environmental protection with very high precision. Depending on the type of land cover classification, it is necessary to choose satellite images of appropriate spatial and temporal resolution. The advantage of supervised classification is that the operator has control over the selected menu of information categories provided for a particular area, and allows the classification to be performed using multitemporal data. The shortcomings of supervised classification certainly include the human factor that is prone to error. Unsupervised classification is automated, facilitates the work of analysts, reduces the space for human error, and does not require a thorough knowledge of the image being processed. The shortcomings of unsupervised classification stem mostly from the difficulty of categorizing classes into information categories that accurately represent land cover. In order to increase the accuracy in land cover analyses, it is necessary to develop automatic methods that rely on a combination of supervised and unsupervised classification methods that enable automatic determination of samples for conducting supervised classifications.

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