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ASSESSMENT OF CLASSIFICATION AND POSITIONAL ACCURACY OF FOREST BOUNDARIES OBTAINED BY DIFFERENT CLASSIFICATION METHODS

OCJENA TAČNOSTI KLASIFIKACIJE I POLOŽAJNE TAČNOSTI GRANICA ŠUMA DOBIVENIH RAZLIČITIM METODAMA KLASIFIKACIJE

Mirnes Bojić, Mladen Jurišić, Dorijan Radočaj, Admir Mulahusić

ABSTRACT

Certain remote sensing methods have become indispensable in forestry for the purposes of forest management, forest inventories, temporal analyses and mapping of changes, coverage assessment, disease analysis, fire analysis, etc. Therefore, it is essential to know the quality of the remote sensing data available for these tasks. This research aims to show the results, in terms of classification accuracy and positional accuracy of forest boundaries, produced by different classification methods when using Sentinel-2 satellite imagery. To assess classification accuracy, standard assessment methods using an error matrix were used, and for assessing the accuracy of forest boundaries, a method for assessing the positional accuracy of digitization and generalization in cartography was used. The extensive analyses conducted as part of this research highlight the advantages and disadvantages of different classification methods.

Keywords: remote sensing, Sentinel-2, forest classification, assessment of classification accuracy, assessment of positional accuracy

SAŽETAK

Pojedine metode daljinskih istraživanja postale su nezaobilazne u šumarstvu za potrebe upravljanja šumama, inventura šuma, vremenskih analiza, kartiranja promjena, procjene stepena zastupljenosti, analize oboljenja, analize požara itd. Stoga je neophodno znati sa kakvom kvalitetom podataka daljinskih istraživanja se raspolaže kod navedenih radova. Ovo istraživanje za cilj ima pokazati kakve rezultate, u smislu tačnosti klasifikacije i položajne tačnosti granica šuma, daju različite metode klasifikacije pri korištenju Sentinel-2 satelitskih snimaka. Kod ispitivanja tačnosti klasifikacije korištene su standardne metode ocjene tačnosti pomoću matrice grešaka, a kod ocjene tačnosti granica šuma korištena je metoda ocjene položajne tačnosti digitalizacije i generalizacije u kartografiji. Veliki broj analiza koje su napravljene kroz ovo istraživanje pokazuje prednosti i nedostatke različitih metoda klasifikacije.

Ključne riječi: daljinska istraživanja, Sentinel-2, klasifikacija šuma, ocjena tačnosti klasifikacije, ocjena položajne tačnosti

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1 INTRODUCTION

Remote sensing imagery, in the form of satellite and aerial photogrammetric images, has become an essential tool in resource management across numerous fields of scientific research (Weih and Norman 2010). The use of medium spatial resolution satellite imagery is often employed for mapping vegetation cover (Tuno et al. 2017). Today, remote sensing methods represent one of the most important ways of collecting spatial data in many activities, and their application in forestry primarily aims to improve existing operational data collection methods in forest inventories (Balenović et al. 2017). Additionally, remote sensing in forestry is used as a high-quality and irreplaceable basis for: management, temporal analyses, mapping of changes, assessing stand density, disease analysis, fire analysis, and more.

Image classification is one of the most important procedures in processing remote sensing imagery and represents the link between remote sensing and geographic information systems. From a raster image, which is suitable as a base for various displays and visual analyses, we obtain a quantitative layer that can later be used for analyses in geographic information systems (Oštir and Mulahusić 2014). Given that classification data are generally and as a rule used as a basis for various analyses and making important decisions, it is essential to understand their quality — as relying on data of unknown accuracy may lead to serious negative consequences. The quality of classified geospatial objects is usually determined within satellite image classification software, which has built-in algorithms for accuracy assessment (Oštir and Mulahusić 2014).

The assessment of classification quality is performed based on an error matrix, which is a tabular representation comparing classified values with reference values. The drawback of this accuracy assessment method is the absence of data on the absolute positional accuracy of the classified objects, so an additional method to assess absolute positional accuracy. The most important aspect of assessing the absolute positional accuracy of classified objects is the precise identification of the same object on the image and the reference object. In the absence of standards for determining the absolute positional accuracy of classified objects, it is appropriate to use methods and algorithms for assessing the accuracy of digitization and generalization in cartography or other similar algorithms and methods.

This research aims to examine the of applicability of satellite imagery and the possibilities of applying different satellite image classification methods. Three classification methods were used in the research, and classification results for each method are presented, accompanied by assessments of both classification accuracy and positional accuracy. The obtained results indicate the advantages and disadvantages of the used methods and show the reliability with which the obtained results can be used.

2 MATERIALS AND METHODS

2.1 Study Area

The investigation of classification and positional accuracy of forest boundaries obtained by different classification methods was conducted in the wider area of the Konjuh mountain, located in the northeastern part of Bosnia and Herzegovina. The subject area is a hilly-mountainous terrain; the lowest point of the analyzed area is at an altitude of about 200 m, while the highest point is the peak of Konjuh mountain with an altitude of 1327 m. Except for a part of Sprečko Polje, which is characteristically flat, the remaining part of the research area is significantly rugged and uneven.

Figure 1. Sentinel-2 image of the study area.

The area of the research site is 14.20 x 27.32 km, or about 475.4 km², of which, according to this research, about 293.4 km² is under forest, which is 61.7% (comprising about 115.3 km² or 24.3% coniferous forest and about 178.0 km² or 37.5% deciduous forest), while the remaining area of about 182.0 km², or about 39.3%, is attributed to other land uses (meadows, arable land, mines, quarries, populated areas, etc.).

2.2 Sentinel-2

The European Commission launched the Copernicus Earth observation program, which is one of the fundamental development programs of the European Union. The Copernicus program is the most comprehensive Earth observation program launched to date (Hećimović and Martinić 2015). The program covers six areas: Land, Marine, Atmosphere, Climate Change, Emergency Management, and Security. The program consists of two components: a satellite component managed by the European Space Agency and an *in-situ* component managed by the European Environment Agency.

The satellite component of the Copernicus program includes several Sentinel satellite missions, six permanent (Sentinel-1, Sentinel-2, Sentinel-3, Sentinel-4, Sentinel-5, and Sentinel-6) and one temporary (Sentinel-5P). All Sentinel missions are based on a constellation of two satellites that meet the requirements for revisit frequency and area coverage.

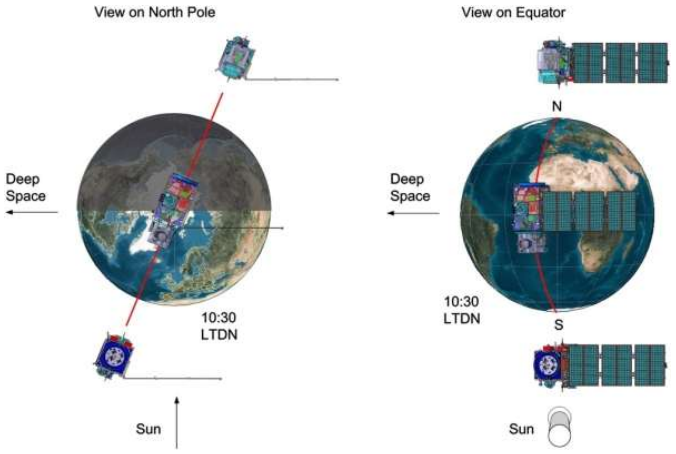

Figure 2. Sentinel-2 orbital constellation (SentiWiki Home, 2025).

Sentinel-2 is a multispectral high-resolution satellite mission for land observation. It consists of two separate satellites, Sentinel-2A launched on June 23, 2015, and Sentinel-2B launched on March 7, 2017, which move in the same sun-synchronous, near-polar orbit with an inclination of 98.62°, phased 180° apart, at an altitude of 786 km. The mission covers the area between 56° south and 84° north latitude, with a temporal resolution at the equator of 10 days with one satellite and 5 days with two satellites.

Sentinel-2 satellites carry multispectral optical instruments that register 13 spectral bands: four bands with a spatial resolution of 10 m (bands 2, 3, 4, and 8), six bands with a spatial resolution

of 20 m (bands 5, 6, 7, 8a, 11, and 12), and three bands with a spatial resolution of 60 m (bands 1, 9, and 10). The optical design of the multispectral instrument allows for a field of view of 290 km.

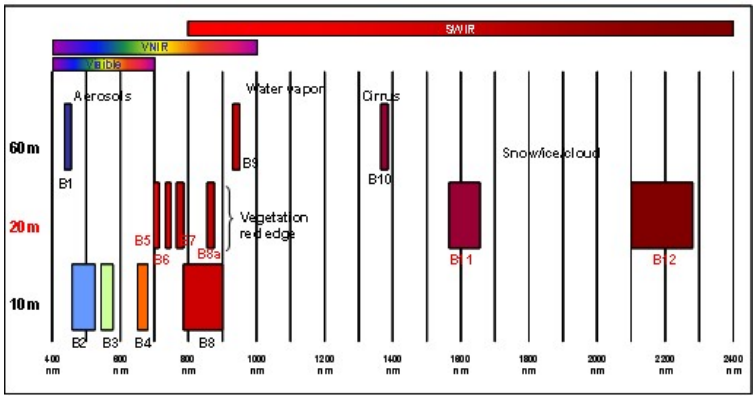

Figure 3. Sentinel-2 spectral channels (SentiWiki Home, 2025).

Sentinel-2 mission data products are available to users at Level-1B, Level-1C, and Level-2A levels and formats.

Level-1B: These are Top Of Atmosphere (TOA) radiance images in sensor projection. They consist of "tiles" representing sub-images of 25 x 23 km, with each tile occupying about 27 MB of memory space. These products require expert knowledge of orthorectification techniques. Pixel coordinates refer to the center of each pixel (Vajsova and Åstrand 2015).

Level-1C: These are Top Of Atmosphere (TOA) reflectance images in a fixed cartographic projection (UTM, WGS 84). Level-1C images are "tiles" of 100 x 100 km, each occupying approximately 500 MB of memory space. These products have applied radiometric and geometric corrections (including orthorectification and spatial registration). Pixel coordinates refer to the upper-left corner of the pixel (Vajsova and Åstrand 2015).

Level-2A: These are Bottom Of Atmosphere (BOA) reflectance images in a cartographic projection. This product is processed by the user using the Sentinel-2 Toolbox software package (Vajsova and Åstrand 2015).

The expected accuracy of Sentinel-2 satellite images is 7-8 m (Vajsova and Åstrand 2015), and the images are available 2-3 days after acquisition.

In this study, multispectral satellite images from the Sentinel-2 mission, Level-1C data, were used. The satellite images were taken on July 4, 2017. Since the images cover a large area, much larger than the study area, the study area was clipped during the data preparation phase to facilitate faster and easier data processing. The research and analyses utilized spectral bands with a spatial resolution of 10 m (bands 2, 3, 4, and 8).

2.3 Image classification methods in Remote Sensing

Satellite image classification is the process of assigning all pixels in an image to classes that represent land use types. There are three main methods of satellite image classification:

- Unsupervised satellite image classification,
- Supervised satellite image classification, and
- Object-oriented satellite image classification.

Unsupervised classification is the process of classifying pixels into classes based on their natural groupings in spectral space (Oštir and Mulahusić 2014).

The unsupervised classification process consists of two steps:

- Cluster generation, and
- Class labeling.

Cluster generation, or cluster analysis, is the process of grouping pixels based on their properties. Various mathematical algorithms, such as K-means and ISODATA, are used for grouping clusters. ISODATA is a modified and improved K-means algorithm. The process in which the analyst assigns appropriate labels to individual groups is class labeling.

Supervised classification is a process in which the analyst creates training samples to classify pixels into classes, and the software then applies these samples to the entire image.

The supervised classification process is divided into (Oštir and Mulahusić 2014):

- Creating and editing training samples, and
- Assigning to classes.

Creating and editing training samples is the first and most important step in supervised classification, where the analyst delineates areas (samples) for specific land use types. It is necessary to select homogeneous and sufficiently large samples for all classes. Classification into classes is performed after all samples have been defined; the software compares pixels with the samples and assigns them to the appropriate classes. The quality of the classification is largely dependent on the algorithm used, and popular methods include: the minimum distance method, the parallelopiped method, and the maximum likelihood method. The maximum likelihood method can be singled out as the best among these methods.

Object-oriented classification is a process in which groups of pixels are classified into representative shapes and sizes.

The object-oriented classification process is divided into:

- Segmentation,
- Defining samples,
- Defining statistics, and
- Classification.

Segmentation is the process of forming shapes in the image. The most popular method for image segmentation is multiresolution segmentation, which has proven to be the best as it classifies

based on texture, context, and geometry. Defining samples and statistics are steps where, similar to supervised classification, areas on the image are selected to define land use samples for classification, and statistical parameters for classification are defined (scale, color/shape ratio, compactness, etc.). Classification is the step where the software, based on predefined samples and statistics, assigns segments to the appropriate classes.

In this study, the ISODATA method was used for unsupervised classification because attempts to use the K-means method yielded results that were significantly worse than those obtained with the ISODATA method. For supervised classification, classifications were performed using several methods, but the best results were achieved with the maximum likelihood method. The maximum likelihood method was also used for the classification of segments in object-oriented classification. It is also important to note that the same training samples were used for both supervised and object-oriented classifications, in order to obtain more representative research results.

2.4 Classification accuracy assessment

After classification is performed, by any method, and pixels are assigned to different land use classes, it is necessary to assess the accuracy of the classification. Assessment of accuracy classification is performed by selecting test points for which the classified values are compared with the actual (reference) values obtained from field observations or by observing larger-scale imagery.

The quality of the classification process is provided by an *error matrix*. This is a table that compares the classification results with reference data and, for each class, gives the number of correctly and incorrectly classified pixels (Oštir and Mulahusić 2014).

Table 1
Error matrix

		Reference Values				
		W1	W2	⋯	Wk	
Classified Values	W1	p_{11}	p_{12}	⋯	p_{1k}	p_{1+}
	W2	p_{21}	p_{22}	⋯	p_{2k}	p_{2+}
	⋮	⋮	⋮	⋱	⋮	⋮
	Wk	p_{k1}	p_{k2}	⋯	p_{kk}	p_{k+}
		p_{+1}	p_{+2}	⋯	p_{+k}	N

There are several ways to express classification accuracy, which can be derived from the error matrix, and the choice of how to express accuracy depends on the needs and the approach to accuracy itself. Some ways of expressing classification accuracy are:

Producer accuracy is calculated as the percentage of correctly classified reference points (Oštir and Mulahusić 2014).

$$P_{Wi} = \frac{p_{ii}}{p_{+i}} \tag{1}$$

User accuracy is calculated as the percentage of correctly classified points relative to the total number of points classified in that class (Oštir and Mulahusić 2014).

$$U_{Wi} = \frac{p_{ii}}{p_{i+}} \tag{2}$$

Overall accuracy is calculated as the ratio of all correctly classified points to the total number of points.

$$O = \frac{\sum p_{ii}}{N} \tag{3}$$

Kappa coefficient is a measure of agreement between the classified points and the reference points (Congalton and Green 2008).

$$K = \frac{N \cdot \sum_{i=0}^{k} p_{ii} - \sum_{i=0}^{k}(p_{+i} \cdot p_{i+})}{N^2 - \sum_{i=0}^{k}(p_{+i} \cdot p_{i+})} \tag{4}$$

During the investigation of classification accuracy, 652 test points were established in the study area, evenly distributed throughout the entire area. The test points were used for four different land use types (coniferous forest – 225 test points, deciduous forest – 191 test points, meadows and pastures – 205 test points, and water – 31 test points). These land uses were not chosen randomly; testing was initially conducted on more land use types, but after several experiments, it was determined that this was the optimal number of classes for this research.

Orthophoto plans at a scale of 1:5000, as well as the researcher's private photo documentation, were used as reference data for assessing classification accuracy and the positional accuracy of classified objects.

2.5 Positional accuracy assessment of linear objects

Positional accuracy is considered one of the main elements of spatial data quality. For linear objects, horizontal positional accuracy, vertical positional accuracy, and shape fidelity can be analyzed (Skopeliti and Tsoulos 2000). Positional accuracy refers to the congruence of an object's position in a geospatial model with the actual position of that object in space (Tuno et al. 2017). The key to accuracy assessment is the precise identification of the same object on the map or image being evaluated and the reference object (Congalton and Green 2008), all to avoid incorrect accuracy estimation and obtaining false information about accuracy.

There are several different standards that govern the assessment of positional accuracy. The standards are based on comparing the coordinates of points measured in the dataset whose accuracy is being assessed with the corresponding reference coordinates. The situation is much more complicated for lines and polygons, as their deviations are a set of positional errors that vary along the line (Tuno et al. 2017).

In the case of assessing the positional accuracy of class boundaries in a classification, the rules for assessing accuracy in digitization and generalization in cartography can be applied. This approach is based on the assessment of two components of linear objects: positional accuracy assessment and shape preservation.

To control the lines, it is necessary to classify them into homogeneous segments. Segmentation is achieved by a methodology that relates to natural characteristics and is based mainly on the variation of fractal dimensions (Skopeliti and Tsoulos 2000).

Horizontal positional accuracy is measured by the deviation from the position of the reference data. It can be estimated by distance measures, such as the average Euclidean distance or the Hausdorff distance between the reference and observed linear features (Skopeliti and Tsoulos 2000).

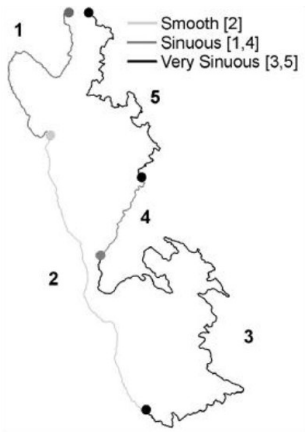

Figure 4. Segmentation of boundary lines (Skopeliti and Tsoulos 2000).

After the classification is performed, regardless of the method used, the results of the classification are areal geometric objects (polygons). To be able to talk about the quality of the classification and to use the classification data, it is necessary, in addition to the classification accuracy assessment, to have data on the positional accuracy of the boundaries of the classified objects (polygons).

Before the accuracy assessment itself, cartographic aggregation of the polygons created during classification was performed, followed by the smoothing of the boundary lines of these polygons. According to the previously described methodology, it is necessary to classify the boundary lines of the classification objects into homogeneous segments and to assess the accuracy for each segment separately.

Given that there is a lot of mixing of different classes in the study area, test samples, i.e., test polygons and parts of polygons, were selected for accuracy assessment. When selecting the test polygons, care was taken to choose them for different types of forests, in order to be able to perform an accuracy assessment for different boundary lines.

A total of 58 test polygons with a total boundary line length of about 50.2 km were selected in the study area, grouped into three target groups: testing the positional accuracy of the boundary between coniferous forest and other non-forest land uses – 23 test polygons with a boundary line length of about 13.1 km; testing the positional accuracy of the boundary between deciduous forest and other non-forest land uses – 18 test polygons with a boundary line length of about 26.2 km; and assessing the accuracy of the boundary between different forest types (coniferous and deciduous) – 17 test polygons with a boundary line length of about 10.8 km.

By analyzing the selected test polygons and boundary lines, it was determined that they are mostly homogeneous in their shape and curvature, and they were all classified into one homogeneous segment – slightly curved boundary lines.

The reference values for the positional accuracy assessment were lines obtained by digitizing from digital orthophoto plans at a scale of 1:5000, thus satisfying the requirement that the comparison be made with data of a higher order of accuracy. The accuracy was calculated as the average Hausdorff distance between the reference and test lines.

The same reference data were used for all three classification methods in both the classification accuracy assessment and the positional accuracy assessment of forest boundaries.

3 RESULTS

The main objective of this research is to show the classification accuracy and positional accuracy results for different forest types produced by different classification methods, using the same imagery and the same software for data processing and classification.

In this study, all analyses were performed in the same software package, *System for Automated Geoscientific Analyses* (SAGA) v5.0.0. For each analysis performed, a large number of repetitions were carried out until the best result was obtained. Also, all analyses in the study were performed by the same operator.

In the process of assessing the accuracy of the unsupervised classification, the results shown in the following error matrix were obtained (Table 2).

Table 2
Error matrix – Unsupervised Classification

		Reference Values				
		Coniferous Forest	Deciduous Forest	Meadow and Pasture	Water	
Classified Values	Coniferous Forest	100	31	0	0	131
	Deciduous Forest	25	64	4	0	93
	Meadow and Pasture	6	93	200	0	299
	Water	94	3	1	31	129
		225	191	205	31	652

By examining the error matrix and different types of accuracy assessment, it is evident that the classification results from the unsupervised method are not satisfactory; in fact, they are far below satisfactory levels. Generally, a classification accuracy above 90% is considered good, and above 80% is satisfactory (Oštir and Mulahusić 2014).

Based on the data from the error matrix, the accuracy parameters for the unsupervised classification were determined (Table 3).

Table 3
Classification Accuracy – Unsupervised Classification

Class	Coniferous Forest	Deciduous Forest	Meadow and Pasture	Water
Number of Test Points	225	191	205	31
Producer's Accuracy	44.4%	33.5%	97.6%	100%
User's Accuracy	76.6%	68.8%	66.9%	29%
Overall Accuracy		61.2%		
Kappa Coefficient		47.5%		

The user accuracy for forest classification is 76.6% for coniferous forests and 68.8% for deciduous forests, while the producer accuracy is significantly lower, at 44.4% for coniferous forest and 33.5% for deciduous forest. In unsupervised classification, the misclassification of coniferous forest as water stands out, which can be a limitation for further use of the classification data. The overall accuracy of the unsupervised classification is 61.2%.

The error matrix for supervised classification indicates that the results of this classification are significantly better than those obtained with the unsupervised method (Table 4). It is also evident that the forest classification is significantly better, and the number of classified values that differ from the reference values is greatly reduced.

Table 4
Error matrix – Supervised Classification

		Reference Values				
		Coniferous Forest	Deciduous Forest	Meadow and Pasture	Water	
Classified Values	Coniferous Forest	189	15	0	2	206
	Deciduous Forest	29	173	1	0	203
	Meadow and Pasture	7	3	204	0	214
	Water	0	0	0	29	29
		225	191	205	31	652

Given that the supervised classification method yielded better results, the individual accuracy types for supervised classification are consequently better.

Table 5
Classification Accuracy – Supervised Classification

Class	Coniferous Forest	Deciduous Forest	Meadow and Pasture	Water
Number of Test Points	225	191	205	31
Producer's Accuracy	84.0%	90.6%	99.5%	93.5%
User's Accuracy	91.7%	85.2%	95.3%	100%
Overall Accuracy		87.4%		
Kappa Coefficient		91.3%		

Producer accuracy for coniferous forest is 84.0%, and for deciduous forest, it is 90.6%. User accuracy for coniferous forest is 91.7%, while for deciduous forest it is 85.2%. These accuracy results indicate that the performed classification can be considered satisfactory. The overall accuracy of the supervised classification is 87.4%.

As expected based on previous research, object-oriented classification yielded the best results. Namely, the error matrix for object-oriented classification shows that this classification has the fewest incorrectly classified test points (Table 6).

Table 6
Error matrix – Object-Oriented Classification

		Reference Values				
		Coniferous Forest	Deciduous Forest	Meadow and Pasture	Water	
Classified Values	Coniferous Forest	205	12	0	1	211
	Deciduous Forest	10	176	0	0	193
	Meadow and Pasture	9	3	205	1	220
	Water	1	0	0	29	30
		225	191	205	31	652

The accuracy of the object-oriented classification (Table 7) shows that this classification is good and offers better results than supervised and unsupervised classification.

Table 7
Classification Accuracy – Object-Oriented Classification

Class	Coniferous Forest	Deciduous Forest	Meadow and Pasture	Water
Number of Test Points	225	191	205	31
Producer's Accuracy	91.1%	92.1%	100%	93.5%
User's Accuracy	94.0%	94.6%	94.0%	96.7%
Overall Accuracy	91.8%			
Kappa Coefficient	94.3%			

In fact, over 94% of the test points for all land use types were correctly classified; specifically, the user accuracy for coniferous forest is 94.0%, and for deciduous forest, it is 94.6%. The producer accuracy for coniferous forest is 91.1%, while for deciduous forest it is 92.1%. The overall classification accuracy using the object-oriented method is 91.8%.

After assessing the classification accuracy, the accuracy of the coniferous and deciduous forest boundaries was investigated.

Table 8
Positional Accuracy of Classified Object Boundaries

Class	Unsupervised Classification	Supervised Classification	Object-Oriented Classification
Coniferous Forest – Other	-	10.4 m	8.7 m
Deciduous Forest – Other	-	11.0 m	10.2 m
Coniferous – Deciduous Forest	-	14.0 m	11.6 m

When attempting to assess the positional accuracy of forest boundaries from the unsupervised classification, it was concluded that it was pointless to assess the accuracy for this method because the classification results were far below satisfactory, and different classes were highly intermixed. Therefore, the accuracy assessment was only performed for the supervised and object-oriented classification methods.

The assessment of the positional accuracy of forest boundaries for supervised classification showed that the highest accuracy of boundary lines was achieved for the boundaries of coniferous forest with other non-forest land uses, with an obtained accuracy of ±10.4 m. Slightly lower accuracy was obtained for the boundaries between deciduous forest and other non-forest land uses, with an accuracy of ±11.0 m. The lowest accuracy was obtained at the boundary between coniferous and deciduous forest, amounting to ±14.0 m.

The accuracy assessment of forest boundaries for object-oriented classification yields better results. For the boundaries of coniferous forest with other non-forest land uses, an accuracy of ±8.7 m was obtained. Poorer results were achieved for the boundaries between deciduous forest and other non-forest land uses, with an accuracy of ±10.2 m.

The poorest accuracy results were obtained for the boundary between coniferous and deciduous forest, with an accuracy of ±11.6 m.

4 DISCUSSION

When analyzing the results of the unsupervised classification accuracy assessment, it was observed that a significant portion of the points identified as coniferous forest was classified as water, a smaller part as deciduous forest, and a very small part as meadow and pasture. Large deviations and classification errors were observed for deciduous forest. Specifically, a large number of points identified as deciduous forest were classified as meadow and pasture and coniferous forest. A particular problem is the fact that the number of points classified as meadow and pasture was significantly higher than the number of points classified as deciduous forest. The majority of points identified as meadow and pasture and water were classified into their respective classes.

From this, it can be said that in unsupervised classification, there is a clear problem with classifying all types of forests, and the most likely reason for this is the very similar spectral signature of different land uses, especially different types of green areas.

The classification performed using the supervised method gives significantly better results and higher classification accuracy, as is evident from the error matrix and accuracy assessment. Depending on which type of accuracy assessment is considered, it can be said that the accuracy of the supervised classification method is satisfactory.

It is not difficult to notice that in the object-oriented classification method, the accuracy of classifying forests relative to other classes is very good. A problem with this classification method arose in classifying different types of forests from each other. In fact, a certain number of points marked as coniferous forest were classified as deciduous forest. This problem could be partially solved by introducing mixed forest as an additional class or by increasing the number of samples for classification.

The results of the forest boundary accuracy assessment for supervised classification showed that the achieved accuracy was slightly lower than expected (7-8 m).

The results of the forest boundary accuracy assessment for object-oriented classification showed that the achieved accuracy for coniferous forest is very close to the expected accuracy (7-8 m), while for the other tested boundary lines, it is slightly above the expected value.

An examination of individual Hausdorff distance measurements between the reference line and the line obtained from classification, especially at the boundary of coniferous and deciduous forest, reveals a relatively high percentage of distances that are close to the maximum value, which led to the lower accuracy of these boundary lines. This again points to the aforementioned conclusion that introducing a mixed forest class should be considered as a possibility to avoid this situation, because at the boundaries of coniferous and deciduous forests, these two species are often genuinely mixed.

Since the problem of distinguishing between different types of forests recurs across all three classification methods, and since there is a problem of reduced accuracy in defining the boundary between coniferous and deciduous forests, it would be useful to conduct a study that would focus fully on the classification of different forest types, thereby finding answers to the problems that arose in this research.

5 CONCLUSION

The preceding research has demonstrated the procedure for assessing classification accuracy and the positional accuracy of forest boundaries for different classification methods.

The assessment of classification accuracy generally yielded results that were expected based on experience and knowledge from other and previous studies. Specifically, the classification accuracy results indicate that unsupervised classification is not satisfactory, supervised classification is satisfactory, and object-oriented classification produced very good results.

A symptomatic issue across all classification methods is that a portion of the coniferous forest points was classified as deciduous forest. The same problem occurs in all classification methods; in unsupervised classification, it is pronounced across all classes, but in supervised and object-oriented classification, it is limited to forests. The most likely reason for this phenomenon lies in the very similar spectral signature of these two forest types and the existence of mixed forests. The solution to this problem could be the introduction of mixed forest as a separate class. It would certainly be worthwhile to investigate and analyze this phenomenon separately, but only for object-oriented classification or possibly also for supervised classification, which yield better classification results.

The assessment of the positional accuracy of forest boundaries gave us accuracy results that are somewhat lower than the expected accuracy, that is, lower than the accuracy specified for the imagery used. Regardless of the results being slightly poorer than expected, it can be said that the obtained accuracy of the classified forest boundaries is exceptionally good, and that the classification results, especially the results of object-oriented classification, can be used for most needs in forestry.

This research has also shown that satellite imagery from the Sentinel-2 mission, which is available for free, can be used with great success in forestry and that the results of processing these images are extremely good.

It is also evident from this research that the object-oriented classification method yields noticeably better classification results than supervised classification, and incomparably better results than unsupervised classification. Unsupervised classification should be avoided when working on more serious and important projects; on such projects, object-oriented classification should be used exclusively.

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Authors:

Mirnes Bojić, Phd candidate*
BNpro doo Sarajevo
Buka 6, 71000 Sarajevo, Bosnia and Herzegovina
E-mail: mirnes@bnpro.ba

Professor Mladen Jurišić, PhD
Josip Juraj Strossmayer University of Osijek, Faculty of Agrobiotechnical Sciences
Vladimira Preloga 1, 31000 Osijek, Croatia
E-mail: mladen.jurisic@fazos.hr

Teaching assistant Dorijan Radočaj, PhD
Josip Juraj Strossmayer University of Osijek, Faculty of Agrobiotechnical Sciences
Vladimira Preloga 1, 31000 Osijek, Croatia
E-mail: dradocaj@fazos.hr

Professor Admir Mulahusić, PhD
University of Sarajevo – Faculty of Civil Engineering
Patriotske lige 30, 71000 Sarajevo, Bosnia and Herzegovina
E-mail: admir_mulahusic@gf.unsa.ba

**Corresponding author / autor za korespodenciju*