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ASSESSMENT OF FOREST RESOURCES BASED ON SENTINEL-2 IMAGES – CASE STUDY DERVENTA, BIH (CADASTRAL MUNICIPALITY OF BREZICI)

PROCJENA ŠUMSKIH RESURSA NA TEMELJU SENTINEL-2 SNIMKI – STUDIJA SLUČAJA DERVENTA, BiH (KATASTARSKA OPĆINA BREZICI)

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SUMMARY

The management of forest resources is complicated due to the complete lack of maintenance and disorganization of the land administration and survey that are decades old. Modern, unconventional monitoring systems are used with the aim of improving the existing records systems and creating a clearer insight into the state of forest resources. This study provides an example of the use of one such system, Sentinel-2. Using the R programming language, the multispectral Sentinel-2 images were classified by the Random Forest classification algorithm. Following the completion of the classifications, the accuracy of the classification was evaluated using the error matrix and the Kappa value. An analysis of forest resources for one cadastral municipality was accomplished using classified rasters and data from the Real Estate Cadastre Database. Based on the data analysis, major changes are visible in terms of the abandonment of agricultural land and its conversion into a certain form of forest vegetation. Furthermore, based on these data, the study demonstrates changes that can be monitored in shorter time intervals. Sentinel-2 images can be used to determine forest expansion, based on the aforementioned analyses, resulting in a clearer and better representation of existing forest resources that are unknown due to outdated and unreliable land administration systems.

KEY WORDS: Sentinel-2, Real Estate Cadastre Database, Random Forest, forest

INTRODUCTION
UVOD

Monitoring of LULC (Land Use/Land Cover) changes has a significant impact on managing land use and offering specific subsidies that would significantly improve life quality (Szostak et al. 2018). Land Use refers to the way that land is utilized by humans, and Land Cover represents the physical characteristics of the land surface. Analysis of the data on land use and land cover, allows the identification of opportunities for optimizing land use, such as prioritizing efforts to conserve and develop strategies for the protection and restoration of forests, as well as the potential to discover new forest resources and their optimal utilization

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(Rawat and Kumar 2015). In the context of outdated, decades-old systems and surveys, land management and knowledge of acceptable vegetation resources are not viable. Economic development of any country or region depends on the regulation of land administration and land-legal relations since it enhances the possibility of future investments, which are extremely challenging in situations where the system is entirely out of date and disorganized (Macanović and Đurić 2018).

The lack of up-to-dateness and inconsistency of the cadastral records that are under the jurisdiction of the Republic Administration for Geodetic and Property-Legal Affairs with the actual situation is shown by the simple fact that there is a census cadastre in certain parts of it. The census cadastre is still in force in 9 local self-governance units, i.e. in 107 cadastral municipalities, representing about 7.3% of the entire territory of the Republic of Srpska, which is one of two separate entities of the state BiH (Bosnia and Herzegovina). On the other hand, the land cadastre based on the Austro-Hungarian survey from the 19th century is still present in some municipalities in this entity (RUGIPP 2021).

In the Republic of Srpska, efforts are being made to establish a real estate cadastre covering the entire country. The establishment of the real estate cadastre as a unique record is carried out through the process of public presentation of data on real estate and the holders of those rights. The costly and time-consuming process is expected to result in a single record that enables it to transfer real estate in legal transactions. It is expected to establish a real estate cadastre on approximately 64.1% of the Republic of Srpska territory by 2025 (RUGIPP 2021).

To monitor the real state of resources, the possibilities of using unconventional, modern LULC monitoring systems, such as remote sensing (Li et al. 2019) and Sentinel-2 images (Dobrinić et al. 2019; Phiri et al. 2020) are being investigated. The public remote sensing data are based on a policy of open access and play a crucial role in monitoring changes in forest resources as well as other ecosystem processes, especially in developing countries with limited access to remote sensing data (Turner et al. 2015).

Copernicus enables the use of data from a constellation of satellites (Sentinel) and other missions (commercial and public satellites). The launch of Sentinel-1A in 2014 (Torres and Davidson 2019) initiated the process of establishing a complete constellation of 20 satellites in orbit by 2030. Today, there are six Sentinel missions. Each mission focuses on a different aspect of Earth observation; Atmospheric, Oceanic, and Land monitoring, and the data is of use in many applications (The European Space Agency 2022). Copernicus's services are divided into six thematic areas: services for land management, services for the marine environment, services related to the atmosphere, services to aid emergency response, services associated with security, and services related to climate change (Aschbacher 2017). Studies (Barakat et al. 2018; Bucha et al. 2021; Jovanović et al. 2021; Kovačević et al. 2020; Puletti et al. 2018; Svoboda et al. 2022) demonstrate the manner of using Sentinel-1 and Sentinel-2 for investigating losing or expanding forest areas in the reference regions. In the study (Szostak et al. 2018), remote sensing was applied to depict the discrepancy between official records and actual conditions, and the studies (Kabadayi et al. 2022; Stefanski et al. 2014; Visockiene et al. 2019) demonstrate the use of remote sensing for detecting abandoned agricultural land. Sentinel-2 satellites have a wide range of potential applications in forestry and agriculture (Segarra et al. 2020) because of their unique geographical, temporal, and spectral capabilities.

The Sentinel-2 mission, created as part of the Copernicus program, consists of two polar-orbiting satellites: Sentinel-2A and Sentinel-2B, which are located at a mean altitude of 786 km and placed in the same sun-synchronous orbit, phased at 180° to each other (European Space Agency 2012). The satellites are equipped with MSI (MultiSpectral Instrument) (Gascon et al. 2017). Up to 1.6 TB of data are collected, stored, and retrieved by MSI carriers per orbit. The data is delivered to the ground stations. The ground segment consists of a flight control section and a section for downloading, processing, and distributing MSI images. There are 13 spectral channels and spatial resolutions of 10 m, 20 m, and 60 m, with a wide swath width of 290 km. The time resolution is 10 days at the equator with one satellite, and 5 days with 2 satellites under cloud-free conditions, resulting in 2-3 days at mid-latitudes (Drusch et al. 2012). The environmental monitoring program using the constellation Sentinel - 2 images is changing the way issues related to climate change and ordinary life are managed, understood, and solved. Owing to this mission, it is also possible to monitor certain variables such as chlorophyll and water content in leaves, and leaf surface index. It is also possible to use data to monitor the movement of water courses and map risks and disasters.

In order to provide harmonization with the strategic decisions of the EU (European Union), where energy and climate frameworks foresee an increase in the share of energy production from renewable sources to 32% by 2030, a better assessment of forest areas should be the first and probably the most important. Moreover, continuous forest and shrub growth outside of actively managed forests must be included in the carbon storage accounting (EU Regulation 2018/841) (Bucha et al. 2021). In Europe, and particularly in its eastern and central regions, there was a trend of forest area expansion by 0.17 million km^2 between 1990 and 2010 (FAO UN 2010) and a slight decrease in expansion from 2010 to 2020 (FAO UN 2020). The expansion of forests is the result of afforestation and the natural expansion of forests in places where agricultural land has been abandoned. The abandonment of agricultural land in these regions is a consequence of social and political changes such as the disintegration of socialist agrarian policy and the joining of countries to the global market (Kuemmerle et al. 2008).

The use of remote sensing for assessment of forest resources is crucial because forestry engineers and forest institutions cannot rely on existing records from the real estate cadastre to estimate the size of forest resources. Remote sensing provides several benefits, including extensive coverage of the area, continuous and up-to-date availability of images, consistent outcomes that are not influenced by human bias, effortless incorporation with spatial data, cost-efficiency, and accessibility to a broad range of professionals (Lechner et al. 2020).

Machine learning has been used as a tool for processing remote sensing data. Machine learning can be seen as learning by example because it is an automatic approach to creating empirical models based only on data. Unlike the non-parametric approach, machine learning makes no assumptions about the data, its probability distribution, or its functional form. It is used to solve regression and classification problems (Kovačević 2021). The ones that are most often used are Decision Tree, Random Forest, Neural Network and Support-vector machine.

RF (Random Forest) is a technique that builds multiple decision trees, using a randomly selected subset of samples and training variables. RF is based on the idea that a combination of bootstrap aggregated classifiers perform better than a single classifier (Breiman 2001), where the bootstrap component means that each tree is parameterized by a series of randomly selected set of observations with replacement from the training data. Two parameters need to be set in order to produce the RF. The first parameter, Ntree, specifies the number of decision trees to be generated, while the second parameter, Mtry, determines the number of variables to be randomly selected and tested for the best split when growing the trees (Belgiu and Dragut 2016).

When compared to other methods, RF has a low computing complexity and is able to handle big data sets, process thousands of input variables, estimate the importance of a variable in the classification process, and be resistant to noise and limit values (Rodriguez-Galiano et al. 2012).

The RF machine learning technique is implemented in the CAST (Caret Applications for Spatio-Temporal) library for application within the programming language R. This library uses the CARET (Classification And REgression Training) functionalities which represent the most widely used package for model training and prediction using machine learning techniques (Kuhn 2019).

This article focuses on monitoring forest areas and the contradiction between official forest records and the situation on the ground, based on Sentinel-2 data. One cadastral municipality is tested to clarify the true reality of the forest resources in the Republic of Srpska entity. Additionally, to demonstrate how quickly changes take place, changes that happened between 2017 and 2022 in one cadastral municipality are displayed.

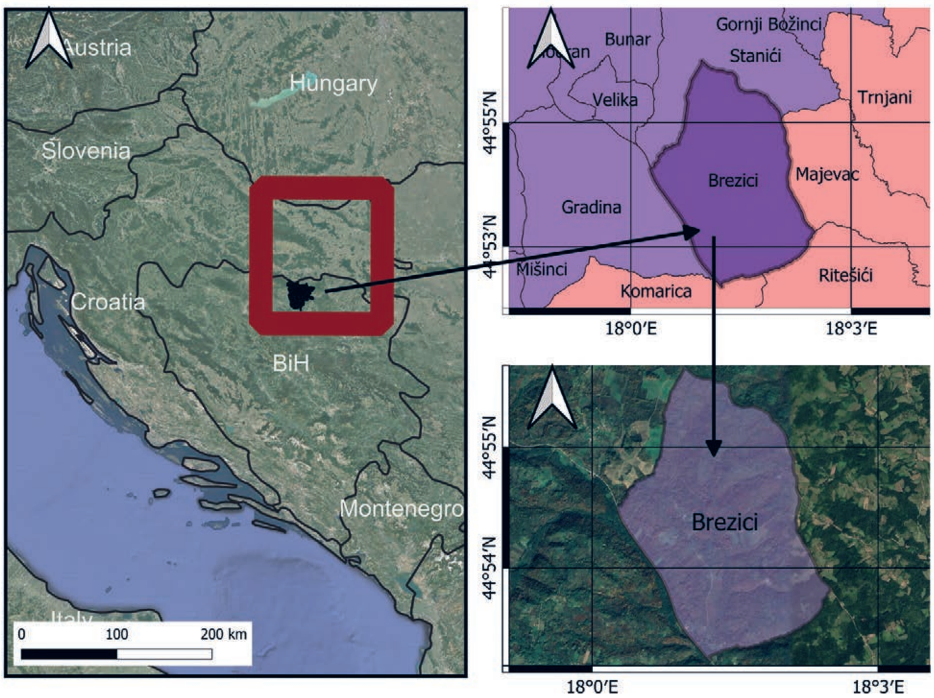

Figure 1. The study area is in Derventa, Bosnia and Herzegovina (cadastral municipality of Brezici).
Slika 1. Područje istraživanja - Derventa, Bosna i Hercegovina (katastarska općina Brezici).

MATERIALS AND METHODOLOGY
MATERIJALI I METODE

Study Area – *Područje istraživanja*

The cadastral municipality of Brezici is located in the southeastern part of the city of Derventa, Figure 1. Various land uses are present in the cadastral municipality of Brezici, and according to data from the cadastre, the largest area is occupied by agricultural fields, followed by forests, meadows, grassland, and orchards. According to data from the Real Estate Cadastre Database, the most represented type of forest is the deciduous forest, covering 185 ha, which is 26% of the total territory. The survey in the city of Derventa was conducted between 1976 - 1977 (RUGIPP 2016).

Input Data – *Ulazni podaci*

Compared to the popular Landsat 8 and other non-commercial satellites, the Sentinel-2 satellites provide more detail in the NIR and SWIR bands, which contributes to the performance of land cover classification for monitoring urban environments, forests, smart agriculture, and many others (ED Chaves et al. 2020).

Sentinel-2 data is available in different processed forms because Sentinel-2 MSI products undergo different stages of processing to reach a level that can be accessed by the users (Phiri et al. 2020): Level – 0, Level – 1A, Level – 1B, Level – 1C and Level – 2A. Level-0 and Level-1A are not accessible to the users, whereas Level-1C (TOA) and Level-2A (BOA) are used for mapping land cover and land use, respectively. The original data for the cadastral municipality of Brezici were taken from the Real Estate Cadastre Database.

Methods – *Metode*

The idea of this study is to show the changes that take place in a small, limited area over appropriate periods, with an emphasis on the emergence of new forest areas and the abandonment of agricultural areas due to accelerated urbanization, which is particularly visible in the areas of former socialist countries. The extended steps of the study are shown in Figure 2. The first step includes downloading Sentinel-2 images for two time periods, 2017 and 2022.

Images were classified in both time series in the same way (described in the next chapter) and the accuracy of both classified images was assessed. Along with the performed classification, as well as for its needs, the NDVI (Normalized Difference Vegetation Index) index was calculated. The classification was performed using the RF algorithm. In addition to Sentinel-2 images, the data from the Real Estate Cadastre Database for a specific cadastral municipality were also used. The downloaded data were classified and converted into raster data to compare them.

Download and processing of Sentinel-2 data – *Preuzimanje i obrada Sentinel-2 snimki*

For this study, Sentinel – 2 (Level - 2A) data were downloaded from the Copernicus Sci Hub platform. The images were downloaded for two-time epochs in August and November 2017, and in May and September 2022, and sorted by spectral channels. We used B2-Blue, B3-Green, B4-Red, B8-NIR (Near-InfraRed) and B6-Red edge, B7-Red edge, B8A-Narrow NIR, B11-SWIR (Short-Wave InfraRed), B12-SWIR in further procedures and analyses. The criterion for

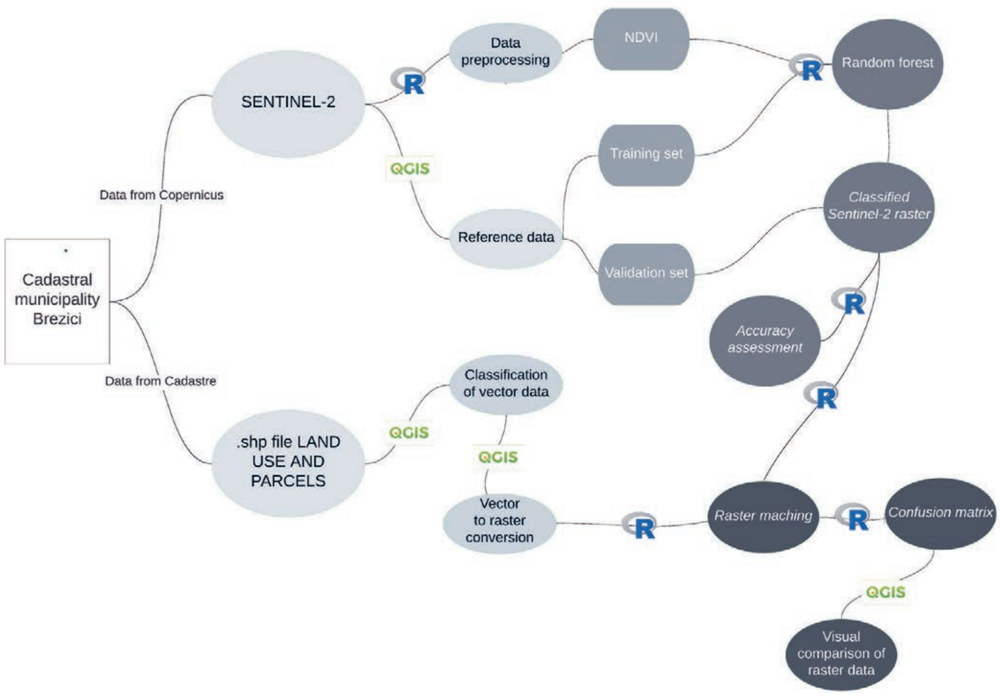

Figure 2. Methodology of creating the paper.
Slika 2. Metodologija izrade rada.

selecting satellite images is for the image to contain little or no clouds and haze, and belong to different seasons in order to discern the phenological phases of plants (Abdi 2020). The matching of the spatial resolution of 20 m with the spatial resolution of 10 m is performed based on the method of the nearest neighbor element in the R programming language. Calculating NDVI, raster classification, accuracy assessment of classifications, and computational analysis of raster differences were performed using the R programming language, whereas QGIS was used for creating training sets, validation sets, and visual analysis.

NDVI was calculated in R based on the quotient of the difference between the red and infrared bands and the sum of those bands (Rouse Jr et al. 1973):

$$NDVI=(NIR-RED)/(NIR+RED), \qquad 1$$

This value represents the normalized difference of vegetation indices and is determined based on spectral values from channels B8 (Near Infrared) and B4 (Red). NDVI values were calculated for both series of images, and one raster representing the difference between the two NDVI images was also calculated.

For the purpose of training, data was prepared from the area sourced from the Copernicus platform. Data preparation was performed in the QGIS software environment. Training data are crucial components in supervised learning and most machine learning algorithms require a large number of training data samples (Abdi 2020). A higher number of carefully selected samples bring better final results. In the area where it is necessary to perform the classification based on the calculated values of NDVI, polygons were drawn according to the previously established classes (forest, other). For each class, about 20 polygons were drawn on different parts of the raster. It was important to consider the size of the drawn polygon to ensure that the given polygons are the best possible representation of the given class. After the preparation of the training set, RF was applied to classify images. The model process has been carried out using loaded training data, predictors, and the desired learning technique, as well as defining metric criteria and determining the best model. The Kappa coefficient was used as a criterion for determining the best model. After cross-validation, it was possible to view the results with the best-obtained parameters through the parameter optimization process.

After the classification was completed, it was important to calculate the accuracy of the results. Accuracy was defined as the degree to which the map produced agrees with the reference classification (Olofsson et al. 2013). Independent data collection was important to determine the accuracy and credibility of spatial information. Therefore, there were two sets of data; the first set was used to create a classification model (training set), which was then applied to the second set (validation set). Performance measures were determined by comparing the classified and reference (known) output classes on the validation data set, which could be represented by a confusion matrix (Kovačević 2022).

Based on confusion matrix, it was possible to calculate various quantitative measures: OA (Overall Accuracy), PA (Producer's Accuracy), UA (User's Accuracy), and Kappa coefficient of agreement (Liu et al. 2007). The Kappa coefficient can have a value from -1 to 1. A kappa coefficient ranging from 0.81 to 1.00 indicates a very good agreement (Miranda et al. 2018).

Data validation was performed in the QGIS software package. Polygons were drawn on the given area independently of the classified raster and training data. The points were intersected with the newly created polygons, and the values for the classified area were obtained. After loading the appropriate data, the confusion matrix and other parameters for accuracy assessment were calculated.

The accuracy achieved by raster classification for 2017 and 2022 is shown in Table 1.

Data from the Real Estate Cadastre Database of Brezici were obtained on October 25, 2022. As input data, .shp files were used, which were manipulated in the QGIS software package. The classification of vector data was performed into two classes: forest, and other. After creating the classes, the vector data were converted into a raster.

Table 1. Achieved classification accuracy of Sentinel images from 2017 and 2022
Tablica 1. Postignuta točnost klasifikacije Sentinel snimki iz 2017. i 2022. godine.

	Sentinel 2017 image *Satelitska snimka Sentinel - 2017*		***Sentinel 2022 image*** *Satelitska snimka Sentinel – 2022*	
Overall Accuracy *Ukupna točnost*	98,90%		99,63%	
Cohen's Kappa *Kohenova Kappa*	0,973		0,991	
Producer's Accuracy *Točnost proizvođača*	other - 99,5% *ostalo - 99,5%*	forest – 97,5% *šuma – 97,5%*	other – 99,5% *ostalo – 99,5%*	forest – 100% *šuma – 100%*
User's Accuracy *Točnost korisnika*	other – 99,0% *ostalo – 99,0%*	forest – 98,7% *šuma – 98,7%*	other – 100% *ostalo – 100%*	forest - 98,7% *šuma - 98,7%*

RESULTS
REZULTATI

The results refer to the visual and digital interpretation of the obtained classified rasters, the interpretation of statistically obtained accuracy indicators, and the final presentation of the difference between the classified rasters.

In the previous chapter were presented the statistically obtained accuracy indicators, indicating the fact that the classification, in relation to the test sample, meets the expected accuracy.

In the first part of the results analysis, a visual and computational overlapping of the rasters of the classified Sentinel-2 images from 2017 and 2022 was performed. The analysis was performed to show the changes occurring in limited areas in short intervals.

Figure 3 shows the difference between the two classified images from 2017 and 2022. The Sentinel-2 images for 2017 were taken in two-time intervals, August and November. Although the choice of recording time intervals is not ideal, it was not possible to choose other intervals due to bad weather conditions during the acquisition. Although there are certain errors in the classified image from 2017, it is possible to decipher certain changes that were visually confirmed based on Google Earth Pro, and presented in Figure 3.

The second part of the analysis compares Real Estate Cadastre Data for the cadastral municipality of Brezici, which was created based on a survey from 1976, to Sentinel-2 images from 2022. Due to the modern, urban life that has been in effect for the last 20 years, changes are happening at a very high rate, which is almost impossible to capture using traditional survey methods. Owing to the development of remote sensing, it is possible to see, with appropriate accuracy, the extent of the changes that have occurred and to propose adequate assessment methods as the next steps. The difference between cadastral data and data obtained from Sentinel-2 images is shown in Figure 4. Table 2 shows the confusion matrix out of which computational conclusions about the difference between these two rasters can be drawn.

Table 2. Confusion matrix representing the pixel difference between the cadastral raster and Sentinel classified raster from 2022
Tablica 2. Matrica konfuzije koja predstavlja razliku piksela između klasificiranih rastera katastra i Sentinel-a iz 2022. godine.

		Sentinel_2022 image *Satelitska snimka Sentinel-2022*	
		Other *Ostalo*	Forest *Šuma*
Cadastre *Katastar*	Other *Ostalo*	18386	31915
	Forest *Šuma*	1003	17174

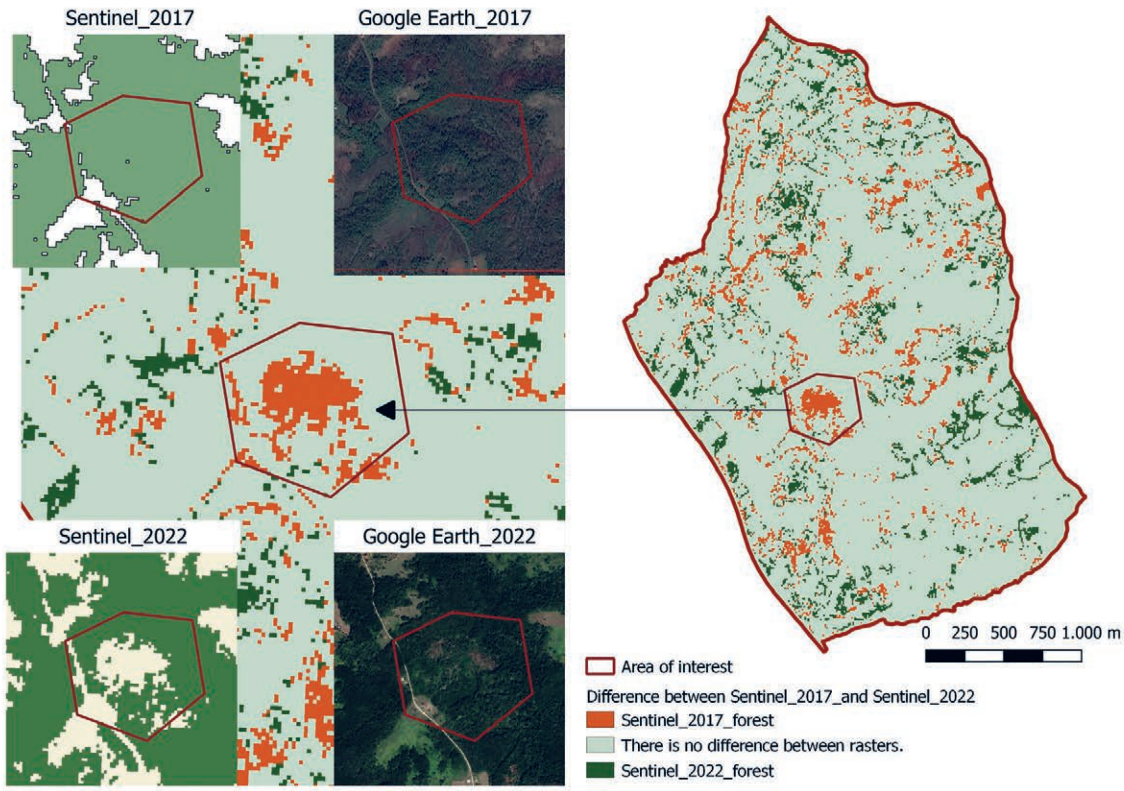

Figure 3. The overview shows the change in vegetation on the Sentinel image from 2017 and 2022
Slika 3. Prikaz obuhvata na kojem je vizualno vidljiva promjena vegetacije na Sentinel snimki iz 2017. i 2022. godine.

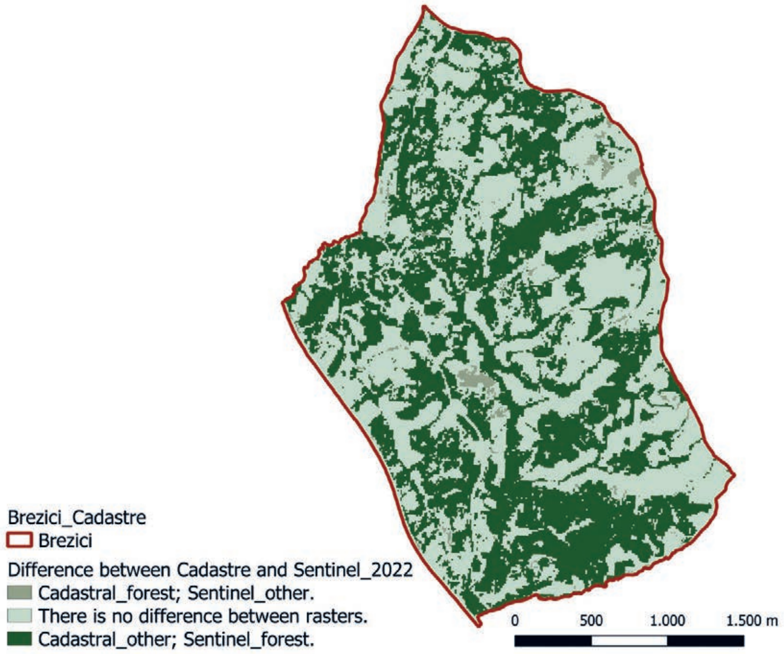

Figure 4. Difference between classified rasters of cadastral data and Sentinel from 2022
Slika 4. Razlika klasificiranih rastera katastarskih podataka i Sentinel-a iz 2022. godine.

The visual assessment of the obtained results was performed in the QGIS software package. Satellite data from Google was used for visual analysis. Satellite data are from the Google Satellite API which has been imported into QGIS as XYZ Tiles**.** Google Satellite API uses the same set of satellite images as Google Earth. This particular data source has been chosen due to its higher spatial resolution in comparison to the images accessible from the Sentinel mission. Google's satellite imagery comes from a variety of sources, including satellite and aerial imagery providers such as DigitalGlobe, TerraMetrics, and GeoEye (Fisher et al. 2012). Google integrates these sources into a single, high-resolution, and regu-

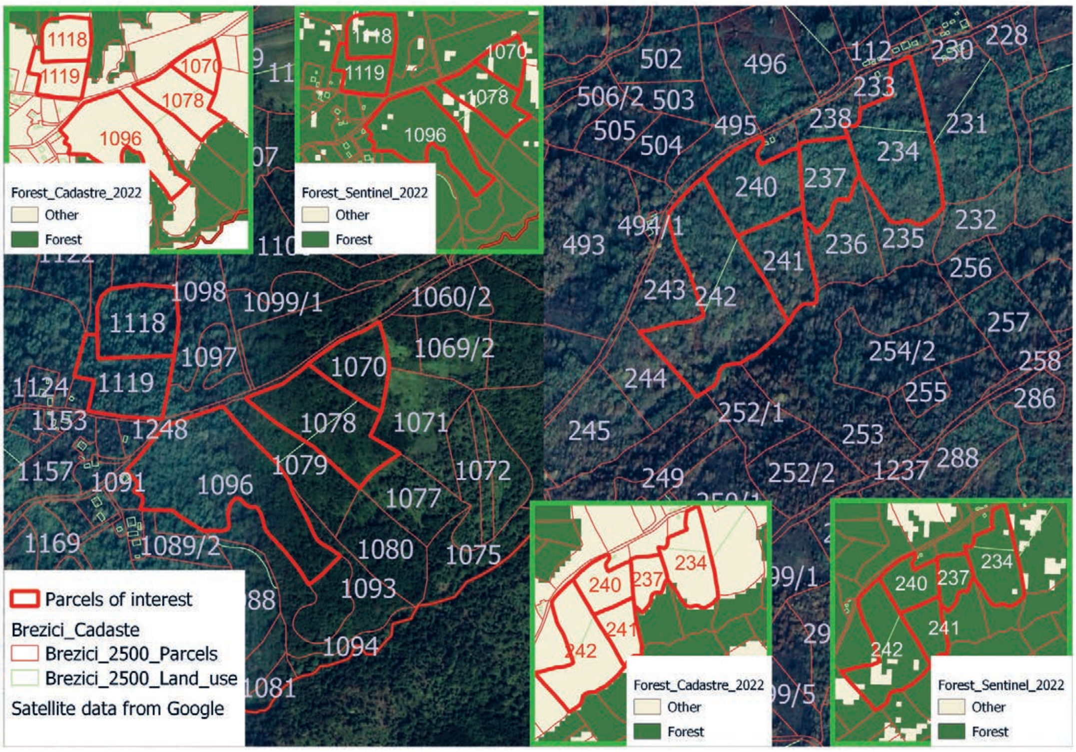

Figure 5. Comparison of Sentinel image, and cadastral data.
Slika 5. Usporedba Sentinel snimke i katastarskih podataka.

Table 3. Land use of parcels in the cadastre, and on Sentinel images.
Tablica 3. Način korištenja parcela u katastru i na Sentinel snimkama.

Parcel number *Broj parcele*	Land use_Cadastre *Način korištenja - Katastar*	Land use_Sentinel *Način korištenja – Sentinel*
234	agricultural field *njiva*	forest *šuma*
237	agricultural field *njiva*	forest *šuma*
240	agricultural field *njiva*	forest *šuma*
241	grassland *pašnjak*	forest *šuma*
242	agricultural field *njiva*	forest *šuma*
1118	grassland *pašnjak*	forest *šuma*
1119	agricultural field *njiva*	forest *šuma*
1096	agricultural field *njiva*	forest *šuma*
1078	agricultural field *njiva*	forest *šuma*
1070	agricultural field *njiva*	forest *šuma*

Table 4. Representation of the area under forests in the cadastre, Sentinel_2017, and Sentinel_2022
Tablica 4. Prikaz površine pod šumama u katastru, Sentinel_2017 i Sentinel_2022.

Units of measure *Jedinice mjere*	Forest Cadastre *Šume Katastar*	Forest Sentinel – 2017 *Šume Sentinel – 2017*	Forest Sentinel – 2022 *Šume Sentinel – 2022*
m^2	1855434	4825168	4857447
%	26	69	69

larly updated global mosaic of imagery that is available through the Google Maps and Google Earth platforms (Google Earth Web and Google Earth Pro Desktop).

Examples of test areas are shown in Figure 5. Based on the given images, it is possible to see the amount of overgrown agricultural land in the area of Brezici. The land use in Table 3 is collected from Real Estate Cadastre Database, and compared to the land use of classified Sentinel-2 images.

After the visual analyses, raster data were converted into vector data to obtain the amount of lost and created forest areas. The final result shows that three times more forest has been deciphered today than was the case in 1976 when a survey was carried out to establish the cadastre, the data which are still used today, Table 4.

CONCLUSION AND DISCUSSION
ZAKLJUČAK I DISKUSIJA

According to the Real Estate Cadastre Database, 26% of the total territory of the cadastral municipality of Brezici is covered in forest, whereas according to the Sentinel-2 images, 69% of the territory is separated under some form of tall vegetation. Of course, the accuracy and spatial resolution of the Sentinel-2 images, as well as significant shortcomings during classification due to the lack of a field-collected training sample, must be considered. However, taking into account all the disadvantages of using Sentinel-2 images, the existence of a huge difference between the real situation on the field and the data from the Real Estate Cadastre Database is unquestionable. The Real Estate Cadastre Database does not accurately reflect the extent of tree and shrub invasion on land where agricultural production has ceased.

The study shows the possibility of using Sentinel-2 images to monitor LULC changes regarding the implementation of EU programs and updating the Real Estate Cadastre Database. Remote sensing and the Copernicus program provide countless free geodata that provide information on the spatial and temporal distribution of land cover (land classes) and the spatial range of vegetation.

Future research should be directed towards developing appropriate training data, which requires going out into the field and allocating appropriate funds for research and determining multiple classes of data, aiming to better classify Sentinel-2 images. By better classifying Sentinel-2 images, in the sense of extracting more classes of data, a more accurate and precise model is obtained that will meet the needs of the Real Estate Cadastre Database updating in a much more detailed scope. Additionally, the use of some commercial satellite images and the financial profitability concerning the conventional ways of establishing the real estate cadastre should also be considered.

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SAŽETAK

Gospodarenje šumskim resurima otežano je u uvjetima potpune neažurnosti i neuređenosti desetljećima starog sustava evidencije i izmjere. U svrhu poboljšanja postojećih evidencijskih sustava i stvaranja jasnijeg uvida u stanje šumskog bogatstva koriste se nekonvencionalni, suvremeni sustavi praćenja. Korištenje daljinskog istraživanja za procjenu šumskog bogatstva je važno, jer se inženjeri šumarstva i šumarske ustanove ne mogu pouzdati u postojeće evidencije preuzete iz katastra nekretnina kako bi utvrdili opseg šumskog bogatstva.

Za demonstraciju korištenja daljinskog istraživanja u svrhu utvrđivanja opsega šumskog bogatstva preuzete su satelitske snimke Sentinel-2 za 2017. i 2022. godinu, kao i podaci iz baze podataka katastra nekretnina k.o. (katastarske općine) Brezici, slika 1. Preuzete multispektralne Sentinel-2 slike klasificirane su na temelju Random Forest klasifikacijskog algoritma, korištenjem programskog jezika R. Tijek procesa obrade podataka prikazan je na slici 2. Nakon završenih klasifikacija, točnost klasifikacije procijenjena je na temelju matrice pogrešaka i Kappa vrijednosti. Parametri točnosti za klasificirane snimke prikazani su u tablici 1. U prvom dijelu analize rezultata obavljeno je vizualno i numeričko preklapanje klasificiranih Sentinel-2 rastera iz 2017. i 2022. godine. Analiza je provedena s ciljem prikazivanja promjena koje se događaju na ograničenim područjima u kratkim vremenskim intervalima, slika 3. Drugi dio analize odnosi se na usporedbu podataka katastra nekretnina za k.o. Brezici nastalih na temelju izmjere i Sentinel-2 snimki iz 2022. godine, slika 4. i tablica 2. Cilj ovog dijela rada je pokazati razliku između stvarnog i katastarskog stanja. Na slici 5. i tablici 3. prikazane su razlike u načinu korištenja između katastra i Sentinel-2 snimki, što ukazuje na promjene nastale napuštanjem poljoprivrednog zemljišta i njegovom prenamjenom u određeni oblik šumske vegetacije. Prema bazi podataka katastra nekretnina, 26% ukupnog teritorija k.o. Brezici prekriveno je šumom, dok je zahvaljujući snimkama Sentinel-2 69% teritorija izdvojeno pod nekim oblikom visoke vegetacije, tablica 4. Analize pokazuju da se Sentinel-2 snimke mogu uspješno koristiti za utvrđivanje obuhvata šuma s ciljem boljeg i kvalitetnijeg prikaza postojećih šumskih resursa koji su nepoznati zbog zastarjelih i nepouzdanih sustava evidencije.

KLJUČNE RIJEČI: Sentinel-2, baza podataka katastra nekretnina, Random Forest, šume