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Land cover changes in Euboea island using Sentinel-2 datasets

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Abstract. The Euboea Island is the second largest island in Greece and has a notable agricultural sector while it is a traditional touristic destination but lately has suffered from extreme wildfires and floods. The scope of the study is to monitor the latest land cover changes in Euboea island after the abrupt environmental disasters caused extended damages in private properties, agricultural sector and infrastructures. The analytic recording of land cover changes was made by analyzing a series of Sentinel-2 satellite multispectral imagery. Moreover, the latest CORINE data product (2018) was used for the selection of the training samples which is crucial for the classification process. The overall accuracy of the classifiers exceeds 85% providing reliable results about the classification procedure. After all analyses, it was concluded that environmental situation in the study domain, the most notable change is the large decrease in forests, especially in the northern part of the island. The agricultural sector has seasonal changes but in general, a small decrease is also depicted. The urban/semiurban class is practically unchanged which indicates - among others - that there is not a significant touristic growth as well as new employment perspectives.

1 Introduction

The transformation of Earth's terrestrial surface due to human activities and natural phenomena are commonly referred to as Land Use/Land Cover Changes (LULCC). This dynamic interplay shapes landscapes on a global scale, supporting the complex interconnectedness of ecosystems and the benefits they provide.

Biodiversity stabilizes the delivery of ecosystem services through time. However, many activities crucial for subsistence living have led to its loss. Loss of biodiversity and the increasing pressures on ecosystem services are significant global challenges. Monitoring the various elements of biodiversity is complex and time consuming. "Land cover change emerges as an invaluable metric, providing a way to examine pressures on ecosystems and biodiversity across different spatial dimensions - from local to the extended global context. Consequently, LULC changes play an important role in the study and analysis of global changed scenario today as the data available on such changes are essential for providing critical input to decision-making of ecological management and environmental planning for future.

Land cover datasets are typically based on observations from satellite-based instrumentation. These instruments are typically passive radiometers that record the electromagnetic radiation of different wavelengths reflected and/or emitted from the surface of the Earth. The raw data are then processed into analysis ready intermediate datasets. Land cover detection is complex. At global scales it requires massive volumes of data and computing capacity. The demand for remote sensing data for land use and land cover mapping has increased with the escalating impact of these changes on terrestrial ecosystems. High-resolution imagery, amended with spatial, temporal, radiometric and spectral dimensions, is sustained by evolving techniques and algorithms that automate and enhance accuracy.

Satellite Remote Sensing and GIS are the most common methods for quantification, mapping and detection of patterns of LULCC because of their accurate geo-referencing procedures, digital format suitable for computer processing and repetitive data acquisition.

Automated land cover classification algorithms develop the capacity to recognize and classify different types of land cover. This training is based on meticulously curated datasets where land cover is meticulously annotated at multiple sites.

This study aims at monitoring the latest land cover changes in Euboea island after the abrupt environmental disasters caused extended damages in private properties, agricultural sector and infrastructures [1-5].

2 Data and Methods

2.1 Study domain

The study domain is Euboea island (Fig. 1) which is the second largest island in Greece, and close to Athens metropolitan area. The study domain has notable touristic activity, important agricultural sector and recently suffered from one the most catastrophic and large wildfires over Greek peninsula (August, 2021).

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Fig. 1. The study domain (yellow rectangle) and its greater area.

2.2 Datasets

Two different types of datasets were used in the study. The first one concerns the multispectral data from Sentinel-2 satellites. More analytically, four bands of these satellite data were used (Table 1). These bands have spatial resolution of 10 m and concern the image scenes of two different dates (29/06/2021 and 26/03/2023).

Table 1. Sentinel-2 bands whose image data were used in the study.

Band number	Central wavelength (nm)
2	490 (VIS-Blue)
3	560 (VIS-Green)
4	665 (VIS-Red)
8	842 (Near InfraRed)

Moreover, two different remote sensing indices were calculated to enhance the spectral separability during the classification process and improve the land cover differentiation. These indices are the normalized difference vegetation index (NDVI) and the Brightness Index (BI).

$$NDVI = (SR_{NIR} - SR_{RED}) / (SR_{NIR} + SR_{RED}) \quad (1)$$

$$BI = [(SR_{RED}{}^{2} / SR_{GREEN}{}^{2}) / 2]^{2} \quad (2)$$

Where SR is the surface reflectance in the different spectral regions (Table 1).

2.3 Methodology

During this study, Sentinel-2 image scenes from three different dates (29/06/2021, 27/09/2021 and 26/03/2023), were selected. In these multispectral images, a series of pre-processing analyses were conducted. These analyses include the calculation of the surface reflectance and the atmospheric correction using the "Sen2Cor" module provided by ESA (REFERENCES) [6]. In the following step, a set of different Regions of Interest (ROIs) was selected to represent the main land cover types in the selected satellite images (Table 2). At this point it is mentioned that for the same classes, different ROIs were selected in order to be more representative in each image scene and express clearly the seasonal/monthly land cover changes, especially in the agricultural areas and the arable land which is included in the class ("multiple vegetation") [7].

Table 2. Regions of Interests (ROIs) were selected in the different dates, were examined.

Land cover types	Number of pixels	Image color
Mixed forest	47.010 (29/06/2021) 40.857 (27/09/2021) 40.857 (26/03/2023)	Green
Water surface	2.562 (29/06/2021) 2.562 (27/09/2021) 2.562 (26/03/2023)	Blue
Bare soil	201 (29/06/2021) 6.468 (27/09/2021) 1.489 (26/03/2023)	Magenta
Multiple Vegetation	34.663 (29/06/2021) 34.663 (27/09/2021) 39.484 (26/03/2023)	Yellow
Urban fabric - beaches - rocky areas	3.862 (29/06/2021) 3.862 (27/09/2021) 3.862 (26/03/2023)	Red

Lastly, two algorithms of supervised classification were used, Maximum Likelihood Classification (ML) and Mahalanobis Distance (MD). The results of these two algorithms compared, specifically the regarding their ROI separability and the overall accuracy (OA). The comparative results are shown in following tables (Table 3,4,5 and 6).

Table 3. ROI separability for 29/06/2021

Class	Mixed forest	Water Surface	Bare Soil	Multiple Vegetation	Urban fabric - beaches - rocky areas
Mixed forest		1.99	1.98	1.89	1.99
Water Surface	1.99		1.99	1.99	1.99
Bare Soil	1.98	1.99		1.52	1.99

Multiple Vegetation	1.87	1.99	1.52		1.87
Urban fabric - beaches - rocky areas	1.99	1.99	1.99	1.87	

At this point it is mentioned that the ROI separability is important factor to evaluate the representative choice of different spatial patterns (i.e. land cover types) and finally the classification outcomes. It was found that the independence of the ROIs improved as the separability value between two classes increased. The output values are ranging from 0.00 to 2.00, implying that the ROIs are completely separated when the value is 2.00. For well-separable ROIs, values must exceed 1.9 [8].

Table 4. ROI separability scores for 27/09/2021

Class	**Mixed forest**	**Water Surface**	**Bare Soil**	**Multiple Vegetation**	**Urban fabric - beaches - rocky areas**
Mixed forest		1.99	1.99	1.71	1.99
Water Surface	1.99		1.99	2.00	1.99
Bare Soil	1.98	1.99		1.97	1.99
Multiple Vegetation	1.71	2.00	1.97		1.90
Urban fabric - beaches - rocky areas	1.99	1.99	1.99	1.91	

Table 5. ROI separability scores for 26/03/2023

Class	**Mixed forest**	**Water Surface**	**Bare Soil**	**Multiple Vegetation**	**Urban fabric - beaches - rocky areas**
Mixed forest		1.99	1.89	1.82	1.99
Water Surface	1.99		1.99	1.79	1.99
Bare Soil	1.98	1.99/2		1.87	1.99
Multiple Vegetation	1.82	1.99	1.80		1.90
Urban fabric - beaches - rocky areas	1.99	1.99	1.99	1.90	

At this point, it is mentioned that the overall accuracy was calculated using the confusion matrix in ENVI software.

3 Results

Based on the Corine 2018 classes, new ones are created focused on study area. Exploiting the confusion matrix these classes are grouped enough to create the five main classes that are shown in Table 2. After running different combinations of training samples, we achieved results of the ROI separability for each close to 2.00, which means that the classes are quite different with each other, and good results of the two classifications are expected.

This is confirmed by the results of the overall accuracy and validated using Kappa coefficient (Table 6). The Kappa coefficient shows how much of the error is reduced by the classification algorithm. Meaning that, the maximum likelihood on 27/09/2021 that achieved Kappa coefficient of 0.8220 indicates the classification process avoids 82% of the error that a random classification generates. For the Maximum Likelihood classification, the overall accuracy is satisfactory, without dropping below 80%, as well as the Mahalanobis classification. However, Mahalanobis had higher Overall accuracy [9, 10].

Considering the results of Mahalanobis classification which provide the best overall accuracy in the majority of the examined dates (Table 6) it was found that the mixed forest has the highest land coverage, before and the minimum areal extent just after the wildfire (Fig. 4). On the other hand, multiple vegetation covers most of the land at the year of the fire, and the other two dates has the second highest land cover, after the mixed forest. As anticipated, low vegetation of multiple vegetation class are more visible to the satellites after the fire. The water, urban fabric-beaches-rocky areas remained unaffected. While the bare soil occasionally intertwined with multiple vegetation, particularly in the extensive spring and summer crop seasons. Despite burnt areas, the bare soil class diminished in 2021. This notable change of land cover is evident in Fig. 2 and especially in Fig. 3.

Table 6. Overall Accuracy for Maximum Likelihood Classification and Mahalanobis Distance.

Dates	Algorithm	OA (Percent)	Kappa coefficient
29/06/2021	ML	80.67	0.6905
	MD	81.95	0.7079
27/09/2021	ML	88.39	0.8220
	MD	84.63	0.7532
26/03/2023	ML	80.23	0.6917
	MD	81.82	0.7142

The training sets, classification method, and input spectral bands all have important roles in the creation of land cover maps. The accuracy of the results was improved when the spectral separability of land cover features increases as well as when increase the spectral bands of the satellite images along with suitable remote sensing indices.

From Table 6 is observed that the land cover maps generated from supervised Mahalanobis classification show higher levels of accuracy than of the Maximum Likelihood. Specifically, on the second date (27/09/2021) there is a significant difference with the rest of the dates in overall accuracy. For both of the classification algorithms the Kappa coefficient is higher, and the classification is more accurate, as expected. The cause for these results is the decrease of vegetation, multiple vegetation and mostly mixed forest, less than two months after the wildfire. The data on this date show better ROI separability outcomes, as the burnt area is classified as bare soil and the forest coverage has decreased, so the algorithms do not confuse the types of vegetation.

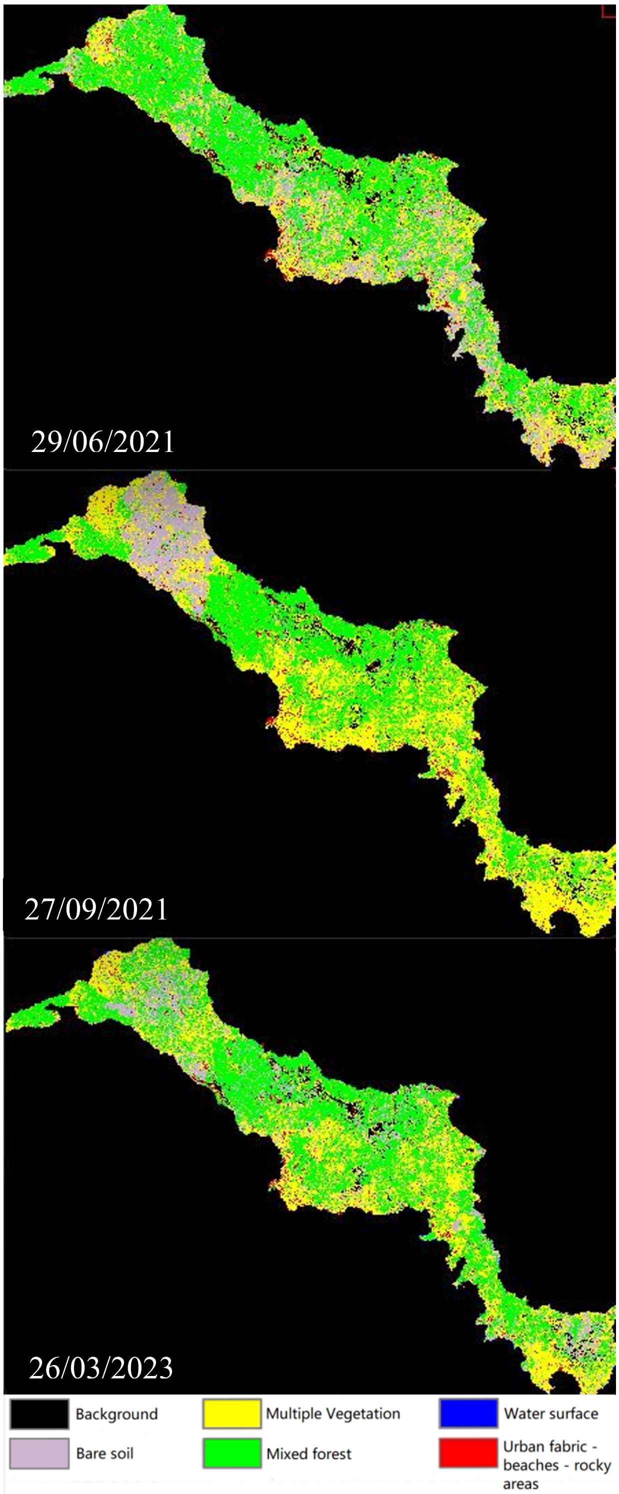

Fig. 2. The LULCC changes in the Euboea island in the three examined dates.

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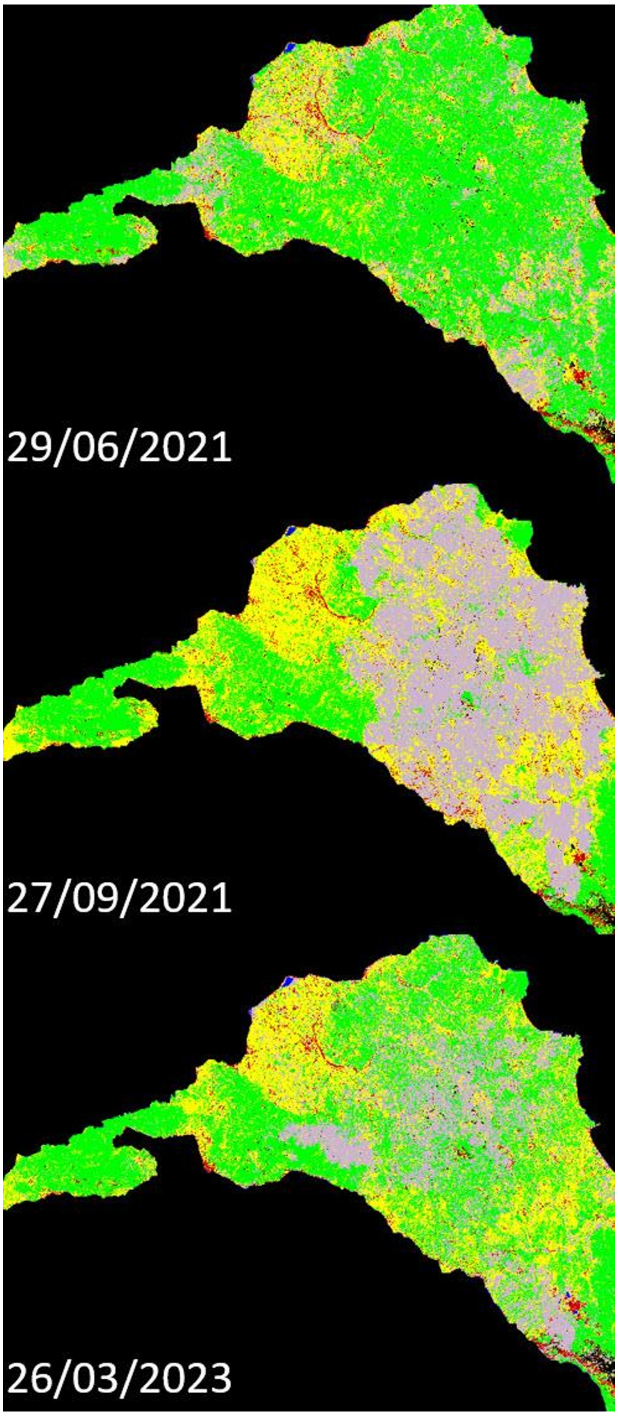

Fig. 3. The spatial change in the three examined dates focused on the northern part of Euboea island where a huge fire existed in the last dates of August 2021.

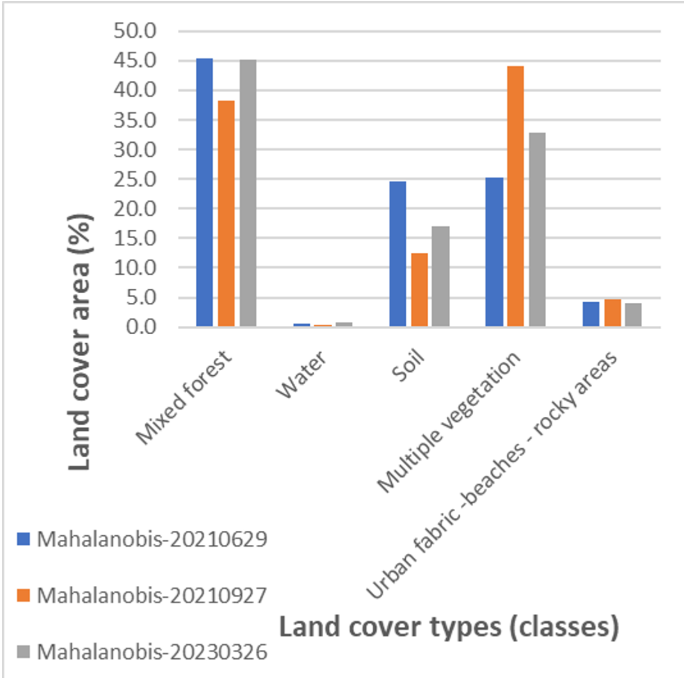

Fig. 4. The LULCC changes in the Euboea island in the three examined dates.

4 Conclusion

The study examines the latest land cover changes in Euboea island after the abrupt environmental disasters due to forest fires caused extended damages in private properties, agricultural sector and infrastructures. The analytic recording of land cover changes was made by analyzing a series of Sentinel-2 satellite multispectral imagery.

It was achieved high scores of overall classification (Table 6) accuracy although the large study area which includes many different land cover types with high seasonal variability. The abrupt large-scale spatial changes of the land cover types were captured in the examined dates, are mainly owed to the large fires of August 2021. The natural environment was started to restore shortly after which is a positive indicator for the conservation of the natural biodiversity of the study area. Also, the seasonal changes of the land types are mainly driven by the agricultural sector and must be always considered in such studies to efficiently delineate areas with of natural environment.

The images that were obtained from Sentinel-2 offer a great level of detail in addition to Corine data that assisted this study. The two classifications showed results of great detail, with the 6-bands layer that were studied (4 bands of 10m, NDVI and BI), offering greater precision which can improve the monitoring of the natural environment, the agriculture and forestry managing, the urban planning and the decision making on a local and regional level.

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