Monitoring Changes in the Prespa Lake Watershed Using Remote Sensing Data

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Abstract

Surface water is one of the most vital Earth resources changing in time and space as a consequence of land use/land cover (LULC) changes, climate change, and other environmental factors. Timely monitoring of the water area and its surroundings is essential for policy and decision-making processes. Monitoring the land cover changes with conventional methods may consume significant time and resources. With the development of remote sensing, land cover monitoring has become practical and effective. The most practical way for monitoring the changes is with the classification of satellite imagery. The main aim of the study is to make a five-year land cover change in a watershed using remote sensing data. For this purpose, two satellite images, from RapidEye-3 and Sentinel-2 have been classified. As a study area, the Prespa Lake watershed has been selected. The Prespa Lake is situated in the Balkan Peninsula and is shared among Albania, North Macedonia, and Greece. For the purpose of the study, a semi-automated object-based classification model has been developed. The results from the classification showed significant accuracy of 93 – 96%. For future studies, it is recommended further investigation, such as using monthly satellite imagery and modeling precipitation and meteorological data.

Keywords: Remote sensing, classification, watershed, change detection.

1. Introduction

In the face of potential climate and land-use changes, studies of the impact of climate and land-use change on hydrology are essential. Taking into consideration the data type, remote sensing plays a big part in this kind of researches. This has been proven over the years where a number of researchers have used both remote sensing and geo-information systems to analyze and model climate and land-use changes. Such analyses can be made for both short and long terms. The changes in land cover can be easily spotted using satellite imagery, and thus relate the hydrology changes with potential risk. Water monitoring is an important part of water resource management, but monitoring the changes and qualities of water bodies with conventional methods may consume significant time and resources.

Surface water is one of the most vital Earth resources changing in time and space as a consequence of land use/land cover (LULC) changes, climate change, and other environmental factors (Feyisa, Meilby et al. 2014). The timely monitoring of the water area is essential for policy and decision-making processes (Morss, Wilhelmi et al. 2005, Giardino, Bresciani et al. 2010). Since the first launch of satellites in the 1970s, remote sensing has been growing as science in every field of study. Water monitoring has become a very important part of remote sensing science since water monitoring plays an important role in water resource management. In the literature, many studies can be found related to water bodies mapping and monitoring (Dörnhöfer and Oppelt 2016, Anderson, Gao et al. 2018). Besides the surface water monitoring, the changes around the water area are significantly important. The most practical way for monitoring the changes is with the classification of satellite imagery. With the development of object-based image analyses in the past few years, the quality of the image classification has been significantly improved. Although generally Object-Based Image Analyses (OBIA) have been mainly used for very high spatial resolution images generally taken from aircrafts or satellites (Hurd, Civco et al. 2005), lately this technique has been also applied to middle and high spatial resolution images for classifying different land covers, where several studies (Esetlili, Balcik et al. , Kaplan and Avdan 2017) reported improvement of the OBIA classification results compared with pixel-based classification. Remote Sensing and geographic data have been successfully applied in different studies, including climate change impacts on hydrology in watersheds (Loi, Tram et al. 2020).

The main aim of the study was to make a five-year land cover change in a watershed using remote sensing data. For this purpose, two satellite images, from two different satellites, RapidEye-3 and Sentinel-2 have been used. As a study area, the Prespa Lake watershed has been selected. Although it is hard to determine the climate change effects in such a short period of time, this paper present a semi-automated classification model, and the changes in the watershed with object-based classification. In order to extract the watershed borders, the digital elevation model has been used. The Prespa Lake is situated in the Balkan Peninsula and is shared among Albania, North Macedonia and Greece with the bigger part belonging to North Macedonia. It is considered to be an ecosystem of global significance and has been identified as one of Europe's major trans-boundary lakes. The Prespa Region hosts unique habitats that are important from both a European and global conservation perspective (BLINKOV and BLINKOVA , Krstić 2012).

2. Materials and Methods

2.1. Study area

Prespa watershed is a high-altitude basin at approximately 850 meters above sea level. It includes two inter-linked lakes: Micro Prespa (47.4 km^2) and Macro Prespa (259.4 km^2). The watershed is shared between North Macedonia, Albania, and Greece with the bigger part belonging to North Macedonia (Figure 1). The lakes, along with the surrounding forested mountain slopes of Pelister, Galichica, Mali and Thate, Varnountas and Triklario, covers area of approximately 140 ha. Most of the Macedonian part of the basin is classified as hilly and hilly-mountainous. Prespa watershed is a high-altitude basin at approximately 850 meters above sea level.

The Prespa region is characterized by a fairly complex geological-tectonic structure, with rocks ranging in age from the oldest Paleozoic formations to the youngest Neogene and Quaternary sediment rocks. The specific orographic conditions that have an impact on the dynamic factors of the climate, together with the impact of geographical and local factors, create three different types of climate throughout the watershed: a warm and cold sub-Mediterranean climatic area; a sub-mountainous and mountainous sub-Mediterranean climatic area; and a sub-alpine and alpine climatic area. The pressures on the water bodies are both natural and anthropogenic in origin. These pressures include the input of pollutants, including nutrients and hazardous substances, and physical pressures on the water bodies, for example, agriculture in the river corridor, drainage, watercourse maintenance, and abstraction.

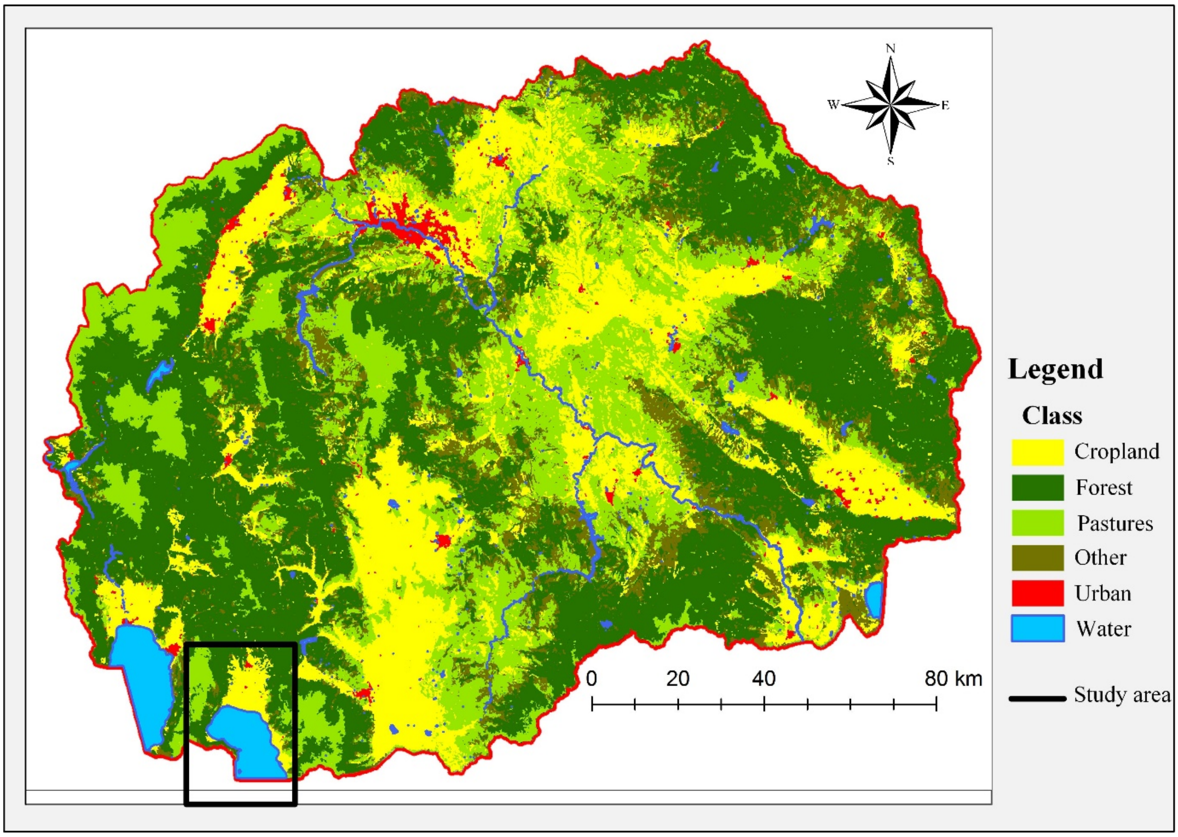

Figure 1. Prespa Lake location in North Macedonia.

In order to extract the borders of the watershed, The Shuttle Radar Topography Mission (SRTM) digital elevation data, an international research effort that obtained digital elevation models on a near-global scale, has been used. The watershed has been extracted with a GIS tool, watershed, wherefrom the digital elevation model a flow direction data has been produced, and a pour point has been selected. The digital elevation model, and the slope, and the boundaries of the watershed are presented in Figure 2.

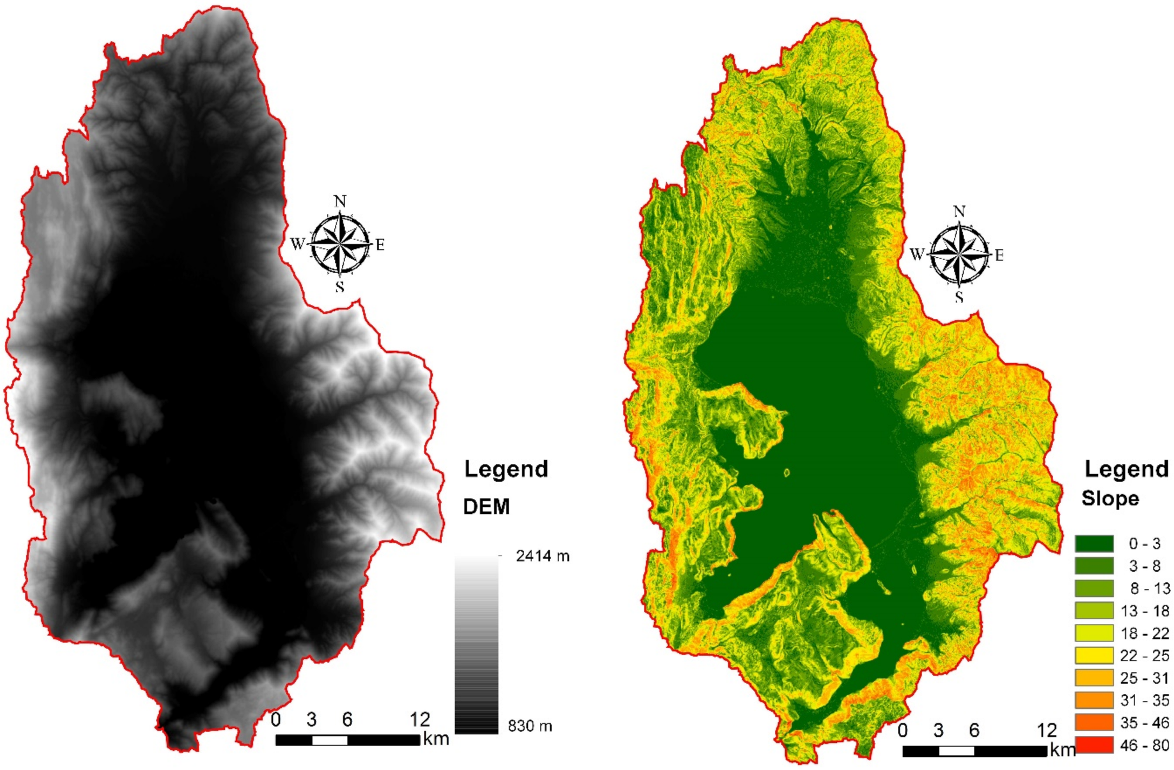

Figure 2. Study area (red border); DEM (left); Slope (right).

2.2. Data

After the extraction of the study area, two satellite images of the study area have been selected and downloaded. In order to get accurate classification, the satellite images were selected to be from the same period. Thus, the first image was acquired with RapidEye-3 in August 2014, while the second image was acquired in August 2019. The RapidEye image was downloaded from the Planet webpage (Team 2017), while the Sentinel-2 image was downloaded from the Copernicus sci-hub. While the Sentinel-2 data are open-source, the RapidEye data were downloaded for scientific purposes.

The images used in this paper are from two different satellites and their data are significantly different. The details about the used data are given in Table 1.

As can be seen from Table 1, the used satellite images have different characteristics. In order to be able to compare the results, only the common bands have been used in the classification. Thus, only five bands from Sentinel-2 have been used (RGB, red edge 1, and NIR). As the images also have a different spatial resolution, the resolution of the RapidEye images has been degraded to 10 m resolution. As an addition to the spectral bands, slope and widely used indices such as Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) were added to the dataset. The images are shown in Figure 3.

Table 1. Sentinel-2 and RapidEye band comparison

Resolution	Center	Band	Center	Resolution
Sentinel-2			RapidEye	
60	443	Coastal aerosol	-	-
10	490	Blue	475	5
10	560	Green	555	5
10	665	Red	658	5
20	705	Red-Edge_1	710	5
20	740	Red-Edge_2	-	-
20	783	Red-Edge_3	-	-
10	842	NIR	805	5
20	865	Red-Edge_4	-	-
60	945	Water vapur	-	-
60	1375	SWIR - Cirrus	-	-
20	1610	SWIR	-	-
20	2190	SWIR	-	-

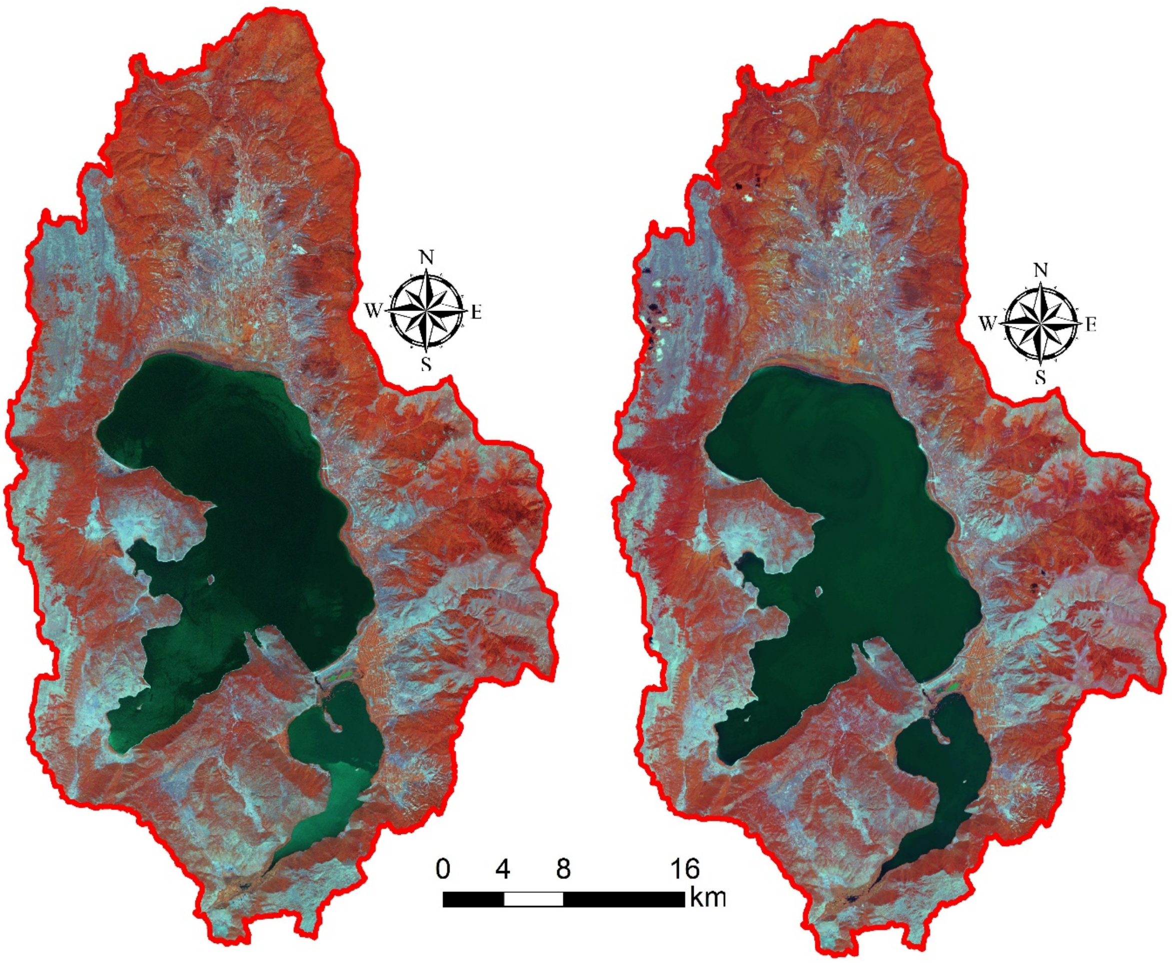

Figure 3. RapidEye image, August 2014 (left); Sentinel-2 image, August 2019 (right).

2.3. Methods

One of the most common methods to obtain land-cover information from satellite images in remote sensing image classification. Image classification converts the data into meaningful information. Depending on the supervision, classifications can be supervised and unsupervised, while depending on the data type, two different classification types can be distinguished: pixel and object-based classification.

The pixel-based classification has been widely used since the revolution of remote sensing in the 1980s. Pixel-based classification uses multi-spectral classification techniques that assign similar pixels in the same class (Yan, Mas et al. 2006). In comparison with pixel-based classification, object-based classification classifies the image based on objects instead of pixels. Although this technique has been introduced in the 1970s, its application in the remote sensing field started a decade ago (Makinde, Salami et al. 2016). Even though this technique has been generally used for high and very high-resolution imagery, it has also been successfully applied in middle-resolution imagery. In comparison with the traditional pixel-based classification technique, several studies have reported the superiority of object-based image classification (Esetlili, Balcik et al. , Kaplan and Avdan 2017). Following the suggestions from the literature review, in this study object-based classification has been performed.

In order to classify the images into seven classes, a semi-automated classification model has been developed. The flowchart of the model is given in Figure 4.

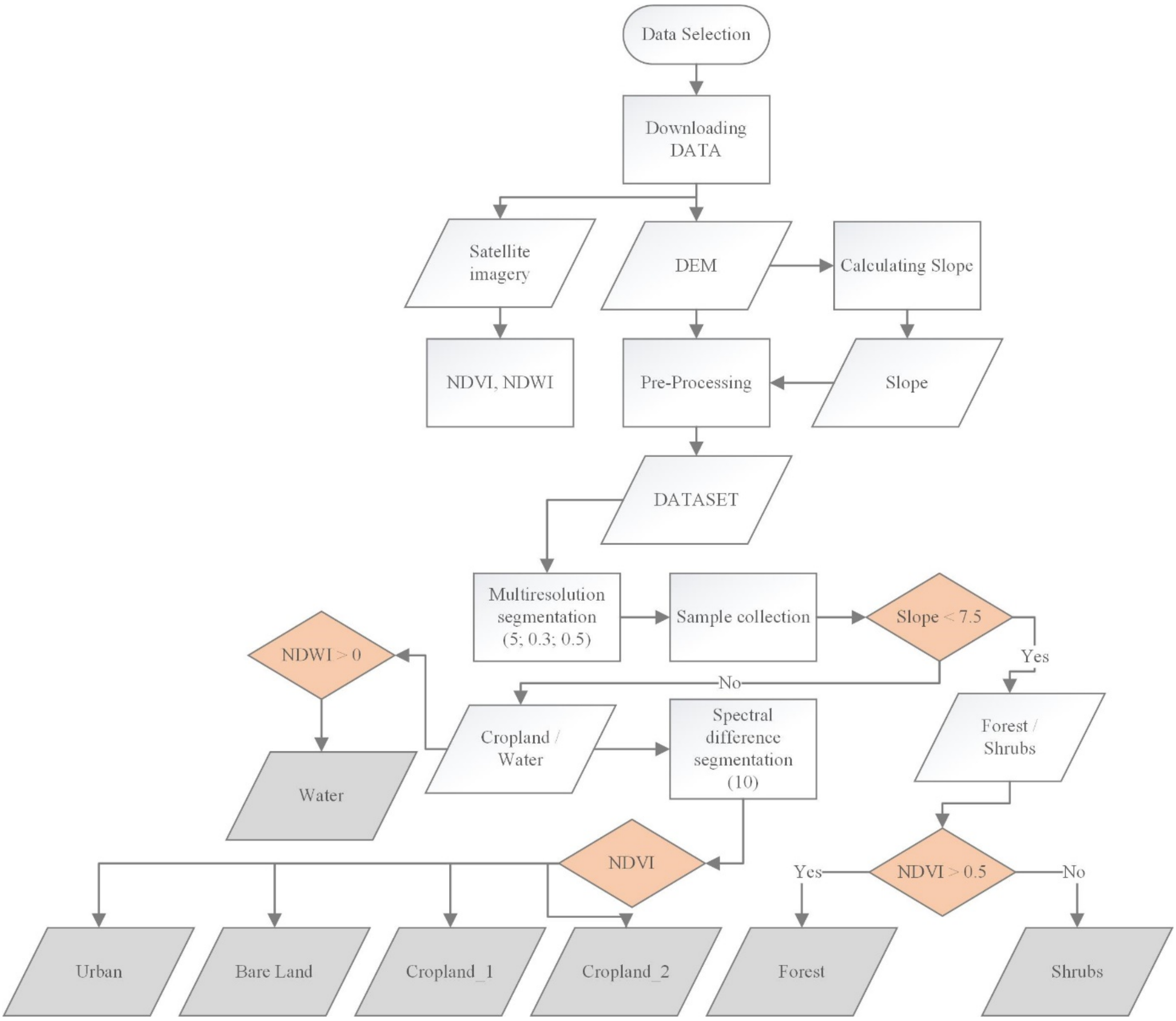

Figure 4. Flowchart of the classification method

Segmentation is the first and one of the most important steps of an object based classification in which the objects are built. With segmentation, the image is decomposed in many relatively homogenous image objects, or segments (Jensen 1996). Objects represent groups of pixels with similar spectral characteristics. In the last decade, image segmentation has been widely used in remote sensing image processing. Thus, several segmentation techniques have been developed. In the developed methodology, two different segmentation techniques have been used, multispectral and spectral difference segmentation. The multiresolution technique starts building a one-pixel object and then grows by merging objects based on the given criteria (Yan, Mas et al. 2006). Before the segmentation, several parameters need to be defined by the user. The image object heterogeneity can be defined as spectral, or shape heterogeneity. The parameters used in this study are given in the flowchart (Figure 4). After the first segmentation, the objects were separated into two different groups. After a sample collection, it was concluded that in the study area, the objects with slope smaller than 7.5% are croplands, while with bigger slope are forest or shrubs. The forest and shrubs classes were separated with tree decisions using NDVI. Afterward, a spectral difference segmentation was made, grouping the object into bigger classes. The Water class was determined using NDWI, while the other five classes were determined using NDVI thresholds.

In this study, eCognition Developer 9 software has been used for the application of the classifications, while ArcMap 10.4.1 has been used for further analyses. In order to be able to compare the results of the different dates, the classifications were performed with the same model. For the accuracy assessment of the classification, random points were scattered over the study area and overall accuracy has been calculated.

3. Results and Discussion

The images used in this study were classified into seven classes, forest, shrubs, barren land, urban area, highly vegetated croplands (Cropland_1), cropland (Cropland_2), and water. The visual results of the classification are presented in Figure 5, while the area of each class is presented in Table 2. The overall accuracy of the classification varies from 94 – 96%.

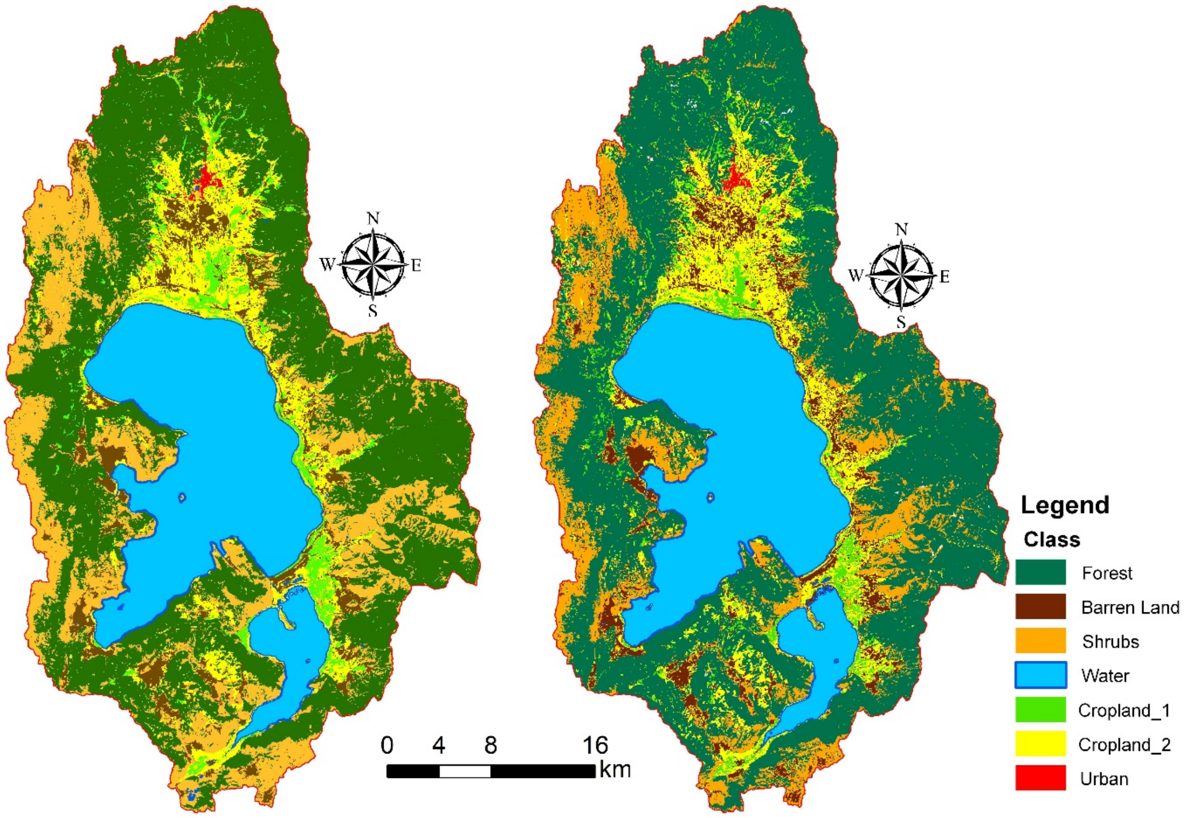

Figure 4. Classification results; 2014 – left; 2019 – right.

Table 2. Classification results 2014 – 2019 presented in ha.

Class	2014	2019
Forest	59842.8	65391.3
Barren Land	7998.2	8397.7
Shrubs	25376.1	16968.4
Cropland_1	4095.6	4983.5
Cropland_2	12146.1	14015.8
Urban	222.1	232.1
Water	29697.0	29389.1

In Figure 5 are presented the class changes between the two years. While there is small or no difference in the forest, barren land, urban, and water classes, there is a decrease in the shrub area and an increase in the cropland classes. However, the change is not significant and can be caused by regular seasonal changes.

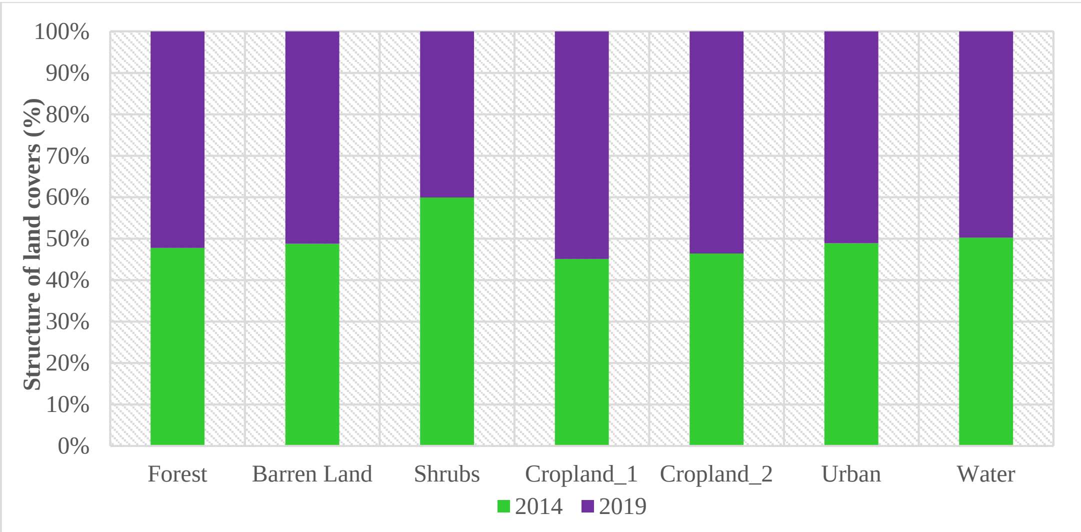

Figure 5. Percentage chart of land cover types in the study area between 2014 and 2019.

The classification analyses did show any significant changes in the land cover of the study area. However, since the local people have been concerned about the water level changes in the late months of 2019, a more detailed investigation is recommended. As an additional investigation, monthly analyses with remote sensing data can be made, using data from the last few months. Also, precipitation and meteorological data should also be taken into consideration. It should be noted that the lake's maximum depth is 54 m, causing any small change in the water area to be visible, forming various wetland areas, especially in the northern part of the lake.

4. Conclusion

The presented study investigates the changes in the Prespa Lake watershed in the period of 2014 – 2019 using satellite remote sensing and geographical data and GIS techniques. The remote sensing data were acquired by RapidEye and Sentinel-2 satellites. The lake is situated in the Balkan Peninsula and is shared among Albania, North Macedonia and Greece with the bigger part belonging to North Macedonia. The lake is considered to be an ecosystem of global significance and has been identified as one of Europe’s major trans-boundary lakes. The Prespa Region hosts unique habitats that are important from both a European and global conservation perspective. In order to meet the main aim of this study, a semi-automated object-based classification model has been developed with a highly satisfying accuracy of 94 – 96%.

The results from the classification did not show any drastic changes in the study area in the investigated period. However, since in the first months of 2020, several locals have been concerned about visible changes in the water area of the lake, we recommend further investigation, such as using monthly satellite imagery, and also the precipitation and meteorological data should be taken into consideration.

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