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MAPPING THREE DECADES WATER CHANGES IN NORTH MACEDONIA USING REMOTE SENSING DATA

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SUMMARY

As the essence of life, water is one of the most important substances on Earth. In the last few decades, the aquatic ecosystem, has been faced with serious challenges due to overuse of water and negative effects of climate change. Thus, water monitoring is essential for water management. In the last few decades, remote sensing and Geographic Information Systems (GIS) has rapidly expanded and evolved as one of the most important tools and technologies in Earth Observation (EO) studies. This paper investigates three decades' water changes in North Macedonia using remote sensing data. For that purpose, Landsat data from five periods during 1988-2019 were used for mapping the water bodies on national level. The water bodies have been classified using Object-Based Image Analyses (OBIA), as well as indices for water bodies extraction, such as Normalized Difference Water Index (NDWI). The results present the water changes on national level from 1988 to 2019 in the summer period in North Macedonia. Although there has been a rise in the water area after 2000 due to dam construction, there has been decrease in the water areas from 2014 -2019. For future studies, more detailed investigation for critical parts of the study area can be applied.

Key words: Water, Remote Sensing, Mapping, Geographic Information.

INTRODUCTION

Monitoring water bodies is an important part of water resource management. However, monitoring the changes and qualities of water bodies may consume significant time and resources. Surface water is one of the most vital Earth resources undergoing changes in time and space as a con-sequence of land use/land cover changes, climate change, and other environmental factors.

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Remote sensing, as a fast growing science in every field, has been widely used for water monitoring (Shao et al., 2019). Also, remote sensing data may be the only source of providing spatially distributed data at multiple scales and on a consistent and timely basis. Remote sensing instruments and techniques provide information for soil and water studies related to ecosystem sustainability, drought mitigation, water balance, and water quality and land use and land cover changes (Feng et al., 2019). Optical remote sensing imagery like Landsat have been used for water bodies monitoring. Landsat legacy has been widely used as a source of data. Starting from 1984, Landsat 5 has been the longest-operating satellite that stopped working in 2011 and has provided many satellite images today used for time-series researchers.
Researchers used Normalized Difference Water Index (NDWI) and other indices for water area changes. NDWI can also be used for calculating loss of water areas. The drought problem caused by climate change has made it necessary to ensure the effective management of water resources.
Combining Landsat imagery with Object-based Image Analysis, and NDWI, in this paper we investigate a three-decade changes on a national level in the Republic of North Macedonia. For this purpose, four Landsat satellite images from four different periods have been used. Starting from 1988, using one of the most historic satellite image over North Macedonia, we compare the water areas from 2000, 2014, and most recently, 2019.

STUDY AREA AND METODS

The Republic of North Macedonia is a landlocked country in the middle of the Balkan Peninsula in Southeast Europe (Figure 1). It covers area of 2,571,300 ha, and shares its boundaries with Serbia, Kosovo, Albania, Bulgaria, and Greece. North Macedonia has approximately 2.1 million inhabitants. Located in the north part of the country, Skopje is the capital with more than 800.000 inhabitants.
The geography of the country is defined by a central valley formed by the river Vardar framed with Shar and Osogovo Mountains. Mount Korab at 2,764 m is the tallest mountain in North Macedonia. Although landlocked, North Macedonia is rich with natural water bodies. Approximately 2% of the total area of the country is covered with water. There are about 35 rivers flowing into the Aegean, Adriatic, and the Black Sea, 53 natural and artificial lakes of which the biggest three are internationally-shared water bodies (Dimitrovska et al., 2012). Vardar, with 388 km length, is the largest river in the country (301 km belongs to North Macedonia). The Vardar basin comprises two-thirds of the territory of North Macedonia, and it plays an integral part in the country's economy and development.

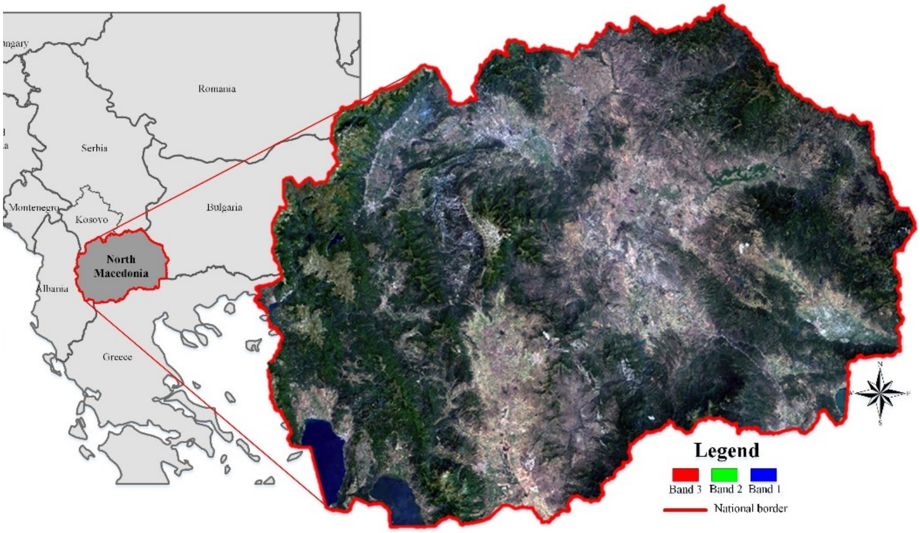

Figure 1: Republic of North Macedonia; Landsat imagery (RGB - 321)

The main aim of this study is to map the water bodies over the territory of North Macedonia in five different periods from satellite imagery. For that purpose, two Landsat 5 and two Landsat 8 images have been used in this study.

Landsat 5 and Landsat 8 are part of the Landsat program, the longest-running enterprise for acquisition of satellite imagery of Earth. The Landsat imagery, archived in the United States and at Landsat receiving stations around the world, are a unique resource for global change research and applications in agriculture (Yin et al., 2018, Yin et al., 2020), cartography (Meneghini and Parente, 2017), geology (Amri et al., 2017), forestry (Matcı and Avdan, 2020), regional planning, surveillance and education, and can be freely downloaded from the 'EarthExplorer' website. Spectral and spatial details about the used imagery are given in Table 1.

Table 1: Landsat imagery details

Landsat 5 TM Bands (µm)		Landsat 8 OLI Bands (µm)	
		30 m Coastal/Aerosol 0.435 – 0.451	Band 1
Band 1	30 m Blue 0.45 – 0.52	30 m Blue 0.452 – 0.512	Band 2
Band 2	30 m Green 0.530 – 0.610	30 m Green 0.533 – 0.590	Band 3
Band 3	30 m Red 0.630 – 0.690	30 m Red 0.636 – 0.673	Band 4
Band 4	30 m NIR 0.780 – 0.900	30 m NIR 0.851 – 0.879	Band 5
Band 5	30 m SWIR-1 1.550 – 1.750	30 m SWIR-1 1.566 – 1.651	Band 6
Band 6	100 m TIR-1 10.40 – 12.50	100 m TIR-1 10.60 – 11.19	Band 10
		100 m TIR-2 11.50 – 12.51	Band 11
Band 7	30 m SWIR – 2 2.090 – 2.350	30 m SWIR – 2 2.107 – 2.294	Band 7
		15 m Pan 0.503 – 0.676	Band 8
		30 m Cirrus 1.363 – 1.384	Band 9

Total of four images have been used in this study. In the period of 1988 – 2019, two Landsat 5 (1988 and 2000), and two Landsat 8 images (2014 and 2019) have been downloaded and pre-processed for water bodies classification. OBIA has been used for classifying the water bodies from the Landsat imagery. In comparison with pixel-based classification, object-based classification classifies the image based on objects instead of pixels. Its application in the remote sensing field started a decade ago (Makinde 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 (Kaplan and Avdan, 2017, Esetlili et al., 2018). First and one of the most important steps of an OBIA is the segmentation. Segmentation is the process in which the objects are built. With segmentation, the image is decomposed in many relatively homogenous image objects, or segments (Jensen, 1996). multiresolution segmentation has been successfully used in segmenting middle-resolution satellite images (Benz et al., 2004). This technique starts building a one-pixel object and then grows by merging objects based on the given criteria (Yan et al., 2006). The criteria parameters used in this study are given in Table 2.

Table 2: Mutli-resolution segmentation parameters

Segmentation Setting	
Image Layer weights	1
Scale Parameter	60
Composition of homogeneity criterion	
Shape	0.5
Compactness	0.5

After the segmentation, a threshold value to the water index NDWI has been applied in order to separate the object containing water from the other land covers. The NDWI formulation has been given below.

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

With a single value threshold, two classes have been assigned, water and other. For the two classes, accuracy assessment has been made.

RESULTS AND DISSCUSION

In order to achieve the spatio-temporal monitoring of surface water dynamics over North Macedonia, in this study, remote sensing data and techniques have been used. The visual results of the analyses are presented in Figure 2. As it can be seen, even the smallest water bodies that can be detected with middle-resolution satellite imagery, have been extracted successfully. Since North Macedonia is small and landlocked country, huge water changes over small periods of time cannot be expected. Thus, the biggest difference in the results, can be noticed between 2000 and 2014, when the Kozjak Dam or the multipurpose hydropower plant of Kozjak has been filled with water in the period between 2003 – 2004. The total reservoir volume is 550 million m^3 (Jovanovska et al., 2016).

The statistical analyses are presented in Figure 3. The visual inspection of the results showed that the developed model extracted the water bodies with high accuracy. According to the statistical analysis, there is positive correlation between the water changes and the time period. However, although it may seem as the water changes have positive correlation over the years on national level, there are many studies in the literature indicating local water losses in several parts of the country.

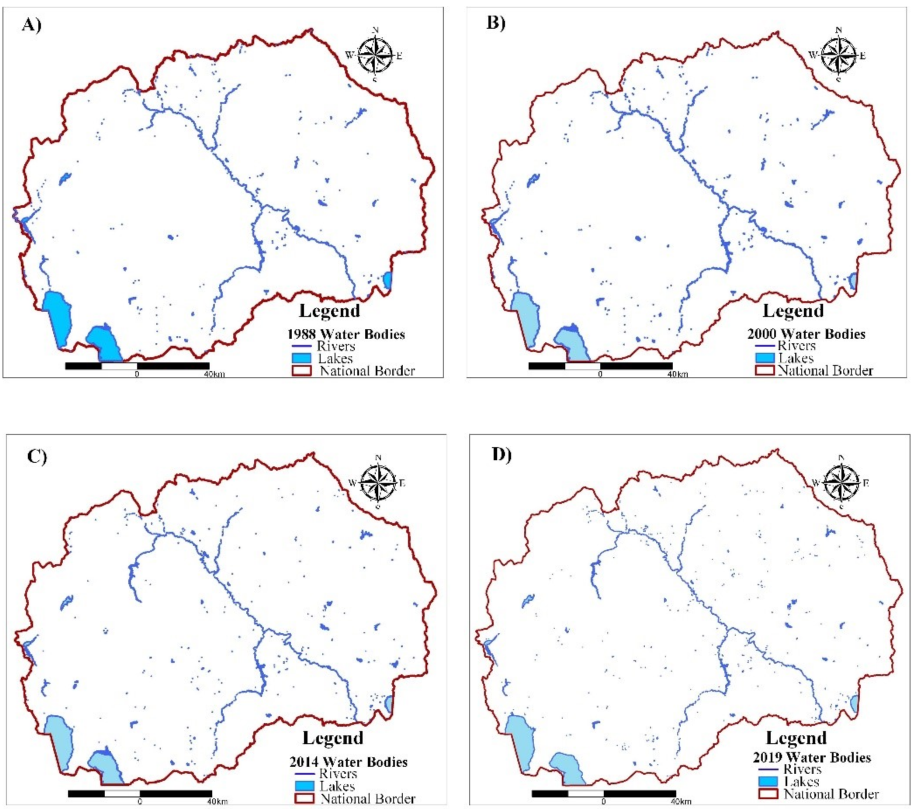

Figure 2: Results; Water bodies in North Macedonia; A) 1988; B) 2000; C) 2014; D) 2019

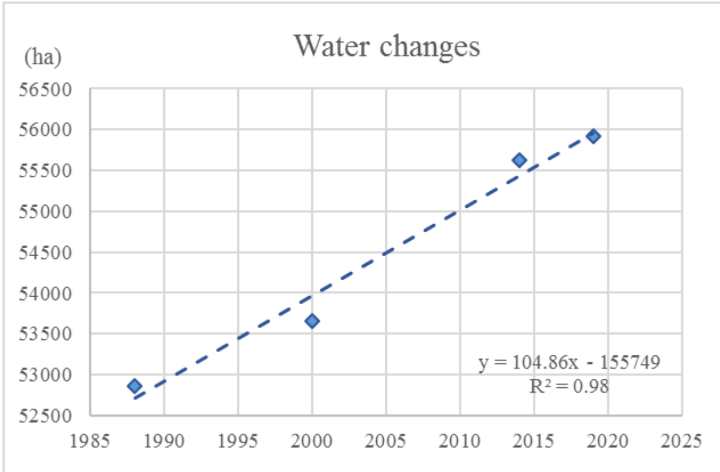

Figure 3. Water area changes over the years.

Kaplan et al. (KAPLAN et al., 2020) investigated the changes in Dojran Lake, and concluded that the lake was at its lowest point in 2002, when slowly, with the support of several projects, gained its old water area in recent years. Another study investigated the changes in the second largest lake in North Macedonia, Prespa Lake (Kaplan, 2020). Also, it should be mentioned that with higher resolution, even more detailed analyses can be made, and smaller water bodies can be detected. However, Landsat's resolution, a middle-spatial resolution, is enough in order to investigate the water changes on national level. As a result of the accuracy assessment made in this study, the accuracy of the water class is higher than 90%. Taking in consideration the full area of North Macedonia, and the water area in 2019, it can be concluded that the water area is covering approximately 2.2% of the country.

CONCLUSIONS

This paper investigates the three-decade water changes on national level in Republic of North Macedonia from 1988 – 2019 using satellite imagery. Four satellite images from four different periods have been used in this study. To the authors knowledge, this is the first study investigating the water changes in North Macedonia using historical satellite imagery as early as 1988. Also, this is the first study that gives clear image about the water cover on national level using remote sensing data. According to the results, on national level, there has been slight rise in the water areas over the years. The main reason for this is the dam construction opened in 2003-2004. The presented results can be of great significances as remote sensed images are a unique source for monitoring the water body changes. This kind of monitoring can be useful in cases where there is not enough available data on the water level changes, and on national level where data collection can be very challenging. For more accurate mapping of the water bodies, in future studies, Sentinel-2 imagery can be considered for the years after 2015.

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