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Large-Scale Mapping of Inland Waters in Google Earth Engine Using Remote Sensing †

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Abstract: Water resources are becoming scarce due to climate change and anthropogenic activity, necessitating immediate action. The first step in conserving our water supplies is to manage them mindfully and sustainably. To achieve this, water sources must be monitored, mapped, and evaluated regularly. Updating national water maps using conventional methods can be a challenging task. Most of the obstacles have been addressed due to recent breakthroughs in the remote sensing field. In this study, we benefit from the remote sensing data integrated into Google Earth Engine (GEE) for developing an application for mapping Türkiye's national inland water bodies. To achieve this, we explored the recently developed Multi-Band Water Index (MBWI) in GEE using Sentinel-2 satellite imagery and then applied it over the research area. The results showed that GEE is a promising application for dealing with large amounts of satellite data and can accurately extract water bodies on a national scale. The results might be helpful for various administrative applications that require up-to-date water information. The developed application can be used over different study areas and for spatiotemporal analysis.

Keywords: remote sensing; water; Google Earth Engine; mapping

1. Introduction

Water sustainability is critical for the well-being of all organisms on Earth and the Earth herself. Water resources are becoming scarce due to climate change and anthropogenic activity, necessitating immediate action. The first step in maintaining our water supplies is to practice conscious management and long-term solutions. Water sources must be monitored, mapped, and evaluated regularly to achieve this. While traditional methods for monitoring water regions are costly and difficult, remote sensing provides an alternative. Remote sensing techniques and data have been employed for more than four decades as an alternative to costly and time-consuming traditional methods for water surface mapping and monitoring. Over the years, many attempts have been made to correctly collect surface water, and researchers are continually creating alternative models for improved accuracy in diverse study locations. The most widely used water extraction index, the Normalized Difference Water Index (NDWI) [1], is based on the difference between the maximum reflectance of the surface water in the green band non-water surfaces in the near-infrared band, has been successfully used in many studies. Several modifications have been made to improve the results [2].

Furthermore, the limitation of the mentioned indices has been resolved with the development of multiband water indices [3-5]. The most recently developed water index is Multi-Band Water Index (MBWI) [6] which outperforms the previously developed indices. Besides indices, several models have been developed for minimizing misclassification noise, such as shadows in urban areas [7] or mountainous regions [8]. Remote sensing data and techniques combined with such indices and models have been used for various water-related studies such as water dynamics monitoring [9], water quality [10], flood mapping [11], etc. It should be noted that most studies are done over small study areas and this limitation is caused by processing big data [12]. Following the recent developments, these limitations can be easily overcome using the cloud platform Google Earth Engine (GEE). GEE, a cloud computing platform, has been used in the past few years for various water studies such as dynamics monitoring [13], surface water extraction and spatio-temporal water changes [14]. In this study, we use GEE for large-scale surface water mapping over Türkiye using Sentinel-2 satellite imagery.

2. Materials and Methods

2.1. Study Area

The Republic of Türkiye is connecting the Euro-Asian continents (Figure 1). It is a peninsula surrounded by three seas: the Black Sea in the north of Türkiye, the Mediterranean Sea in the south and the Aegean Sea in the west. Türkiye has a mountainous and rugged terrain and constitutes approximately 770,760 km² of land and 9,820 km² of water. Among the water areas, Van Lake is the largest natural lake with 3713 km², and Atatürk Dam is the largest artificial lake with 817 km².

Figure 1. Türkiye—Study area.

2.2. Materials and Methods

The European Commission develops Copernicus satellites in partnership with the European Space Agency (ESA). It includes all-weather radar images from Sentinel-1A and Sentinel-1B, high-resolution optical images from Sentinel 2A and 2B, as well as ocean and land data from Sentinel 3 suitable for environmental and climate monitoring. Sentinel-2 is a wide-field, high-resolution, multi-spectral imaging that supports Copernicus Land Monitoring, including monitoring of vegetation, soil and water cover, as well as observation of inland waterways and coastal areas. Sentinel-2 consists of 13 Bands and outperforms the Landsat program in spatial and spectral resolution.

For the purposes of this study, a total of 2806 Sentinel-2 satellite data were used. The Sentinel-2 data was pre-processed based on region, date, and cloud mask filtering. As a result, the imagery was restricted to Türkiye`s borders and dates throughout the summer of 2020, with a 10% cloud filter mask added. Using this method, a clean Sentinel-2 picture collection over Türkiye was produced. Considering the vast study area, a small number of training and testing samples have been selected of the water (90) and non-water classes (190).

MBWI was chosen for water classification since it produced the best results in the literature among index index-based algorithms. MBWI is based on distinctions between water and other low reflectance surfaces, restricting the brightness value ranges used to those in the lower or "darker" section of the terrestrial spectral range characteristic of water. The MBWI is intended to limit non-water pixels while improving surface water information. Wang et al. provide detailed details of the concept [6] and the calculation of MBWI is given in Eq. 1. In addition, to get rid of mountainous shadows that were mistakenly classified as water bodies, we put a threshold of 5% slope over the study area, and areas with higher slope, were automatically excluded from the water class.

$$\text{MBWI} = 2 \times \text{Green} - \text{Red} - \text{NIR} - \text{SWIR1} - \text{SWIR2} \quad (1)$$

In remote sensing analysis, accuracy assessment is a critical evaluator for the results. Thus, in this study, the validation was made using 100 random sample points from the water class. Two measures of accuracy were tested in this study, namely overall accuracy and Kappa coefficient. While overall accuracy gives information about the proportion of the correctly mapped reference sites, the Kappa Coefficient is generated from a statistical test to evaluate the accuracy of the classification. Kappa essentially evaluates how well the classification performed as compared to just randomly assigning values. The Kappa Coefficient can range from -1 to 1. In remote sensing applications with middle-spatial resolution as Landsat, Kappa higher than 0.75 is considered acceptable.

3. Results and Discussion

The study area's surface water bodies were extracted with the employed methodology. As a result, we extracted the water bodies in Türkiye in the summer of 2020. The visual inspection showed that the classification gave good results taken in consideration vast study area. In water extraction studies, the areas with high slope and urban areas are the most challenging, however, the developed algorithm showed good results in these areas as well.

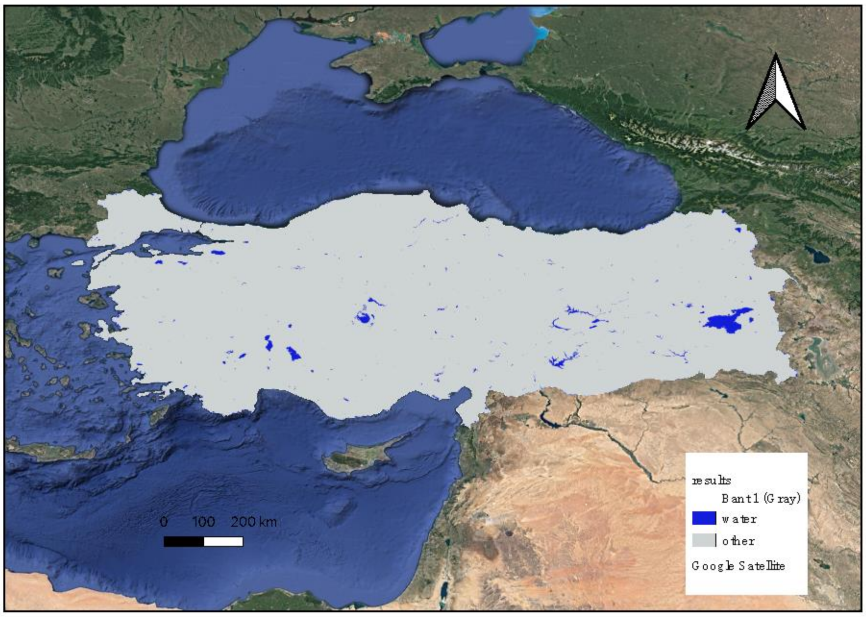

Figure 2. Results.

The accuracy assessment showed an overall accuracy of the water bodies classification of 0.94, meaning that 94% of the water areas, were classified correctly. The kappa statistics gave significant high value of 0.86. For a vast area, the obtained results are acceptable and very important from several points of view. As the methodology is developed in GEE, it can be used repeatedly on different dates, smaller study areas etc., giving fast and reliable information on the water bodies. The water areas can be easily calculated, and spatio-temporal analysis can be made using the same algorithm. With a small modification, the application can be set to use Landsat data, allowing us to analyze the water bodies for 5 decades. Also, here in this study, we classify the water bodies in the summer of 2020. The same application can be used for near-real time applications. The biggest disadvantage in the presented study is the spatial resolution of the used satellite imagery, which is 10 m in this case. This means that the algorithm is only able to classify water bodies that are larger than 10 m, or very small water bodies will not be extracted. However, the obtained results can be useful in various applications and can give the user a clear image of the water bodies over the study area. The results again showed that GEE is a powerful platform able to classify vast areas within a few minutes.

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