



Proceeding Paper

# Large-Scale Mapping of Inland Waters with Google Earth Engine Using Remote Sensing <sup>†</sup>

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**Abstract:** Water resources are becoming scarce due to climate change and anthropogenic activities, 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 employed remote sensing data integrated into Google Earth Engine (GEE) to develop an application for mapping Turkey's national inland water bodies. To achieve this aim, we explored the recently developed Multi-Band Water Index (MBWI) in GEE using Sentinel-2 satellite imagery and then applied it throughout the research area. The results showed that GEE is a promising application for handling large amounts of satellite data and can accurately extract water bodies on a national scale. The results of this study could be helpful for various administrative applications that require up-to-date water information. The developed application can be used for different study areas and for spatiotemporal analysis.

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



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## 1. Introduction

Water sustainability is critical for the well-being of all organisms on Earth and for the Earth itself. Water resources are becoming scarce due to climate change and anthropogenic activities, necessitating immediate action. The first step in maintaining our water supplies is to practice conscious management and implement long-term solutions. Water sources must be monitored, mapped, and evaluated regularly to achieve this aim. 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 continuously 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 and that of non-water surfaces in the near-infrared band, and it has been successfully used in many studies. Several modifications have been made to improve the results [2].

Furthermore, the limitation of the above-mentioned indices has been resolved through the development of multiband water indices [3–5]. The most recently developed water index is the Multi-Band Water Index (MBWI) [6], which outperforms the previously developed indices. In addition to indices, several models have been developed for the minimization of 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 performed across small study areas due to limitations involved in the processing of big data [12]. Following 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 used GEE for the large-scale surface water mapping of Turkey using Sentinel-2 satellite imagery.

## 2. Materials and Methods

### 2.1. Study Area

The Republic of Turkey connects the European and Asian continents (Figure 1). It is a peninsula surrounded by three seas: the Black Sea in the north of Turkey, the Mediterranean Sea in the south, and the Aegean Sea in the west. Turkey has a mountainous and rugged terrain and constitutes approximately 770,760 km<sup>2</sup> of land and 9820 km<sup>2</sup> of water. Among the water areas, Van Lake is the largest natural lake, with 3713 km<sup>2</sup>, and Atatürk Dam is the largest artificial lake, with 817 km<sup>2</sup>.



**Figure 1.** Turkey—study area.

### 2.2. Materials and Methods

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

For the purposes of this study, a total of 2806 Sentinel-2 satellite data points were used. The Sentinel-2 data were pre-processed based on region, date, and cloud mask filtering. As a result, the imagery was restricted to Turkey'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 of Turkey was produced. Considering the vast study area, a small number of training and testing samples were selected from the water (90) and non-water classes (190).

The MBWI was chosen for water classification, since it has produced the best results in the literature among the index-based algorithms. The 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, being

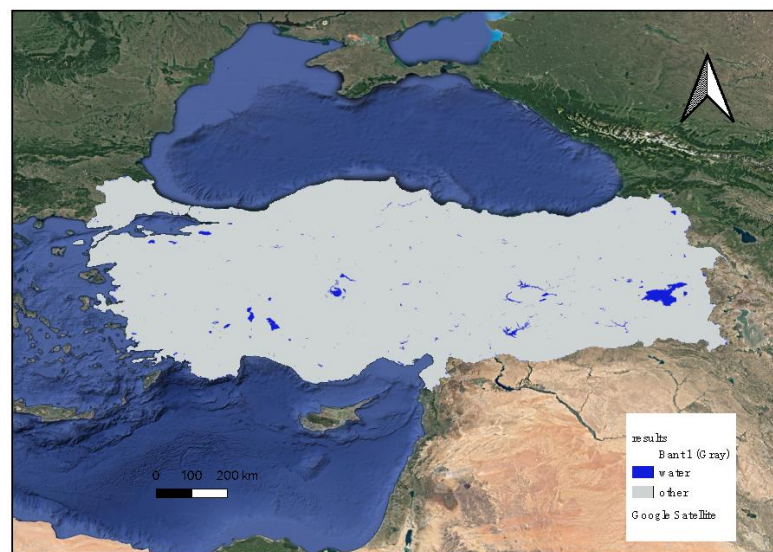
characteristic of water. The MBWI is intended to limit non-water pixels while improving surface water information. Wang et al. provided details of the concept of MBWI [6], and the calculation is given in Equation (1). In addition, to eliminate mountainous shadows that were mistakenly classified as water bodies, we placed a threshold of 5% slope over the study area, and areas with higher slopes 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 performed using 100 random sample points from the water class. Two measures of accuracy were tested in this study, namely, the overall accuracy and kappa coefficient. While the overall accuracy provides information about the proportion of correctly mapped reference sites, the kappa coefficient is generated through a statistical test to evaluate the accuracy of the classification. The kappa coefficient essentially evaluates how well the classification performs as compared to the random assignment of values. The kappa coefficient can range from  $-1$  to  $1$ . In remote sensing applications with a mid-spatial resolution, such as Landsat, a kappa value higher than  $0.75$  is considered acceptable.

### 3. Results and Discussion

The study area's surface water bodies were extracted with the employed methodology. Thus, we extracted the water bodies in Turkey in the summer of 2020 (Figure 2). The visual inspection showed that the classification yielded good results, considering the vast study area. In water extraction studies, areas with high slopes and urban areas are the most challenging; however, the developed algorithm also showed good results for these areas.



**Figure 2.** Results.

The accuracy assessment showed an overall accuracy of  $0.94$  for the water bodies' classification, meaning that  $94\%$  of the water areas were classified correctly. The kappa statistics had a significant high value of  $0.86$ . For a vast area, the obtained results are acceptable and highly important from several points of view. As the methodology was developed in GEE, it can be used repeatedly for different dates, smaller study areas, etc., providing fast and reliable information on the water bodies. The water areas can be easily calculated, and spatio-temporal analysis can be performed using the same algorithm. With a small modification, the application can be set to use Landsat data, allowing one to analyze the water bodies for five decades. In this study, we classified the water bodies in the summer of 2020. The same application could be used for near-real-time applications. The

greatest disadvantage of the present study is the spatial resolution of the used satellite imagery, which was 10 m in this case. This means that the algorithm is only able to classify water bodies that are larger than 10 m, and very small water bodies will not be extracted. However, the obtained results could be useful in various applications and provide the user with a clear image of the water bodies throughout the study area. The results again showed that GEE is a powerful platform that is able to classify vast areas within a few minutes.

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