Long-term spatiotemporal surface water dynamics using Google Earth Engine in southeastern Morocco

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Abstract. Monitoring changes in water areas within arid regions is vital for directing water resource development and ensuring efficient use, and addressing the impacts of drought and climate change. Thus, in this research, we examined the annual changes in surface water at the El Mansour Eddahbi (EME) dam (southeastern Morocco) from 1984 to 2023. To achieve this, we exploited the Google Earth Engine's potential and applied four water indices – MNDWI, EWI, NWI, and AWEI – to Landsat satellite images. Subsequently, for each year, a supervised classification utilizing random forest was implemented to accurately extract and identify water areas. The findings revealed that the EME dam’s water surface area fluctuates substantially on an inter-annual basis. Besides, Pearson’s analysis demonstrates that the EME dam’s water surface area has a strong positive correlation with drought indices such as SPI-12 and SPEI-12. This highlights the link between changing surface water, drought, and the need for adaptive water management under climate change.

1 Introduction

Fluctuations in surface water hold significance for local sustainable development and environmental well-being. The El Mansour Eddahbi dam, which controls the Draa River and is a critical water supply in southeastern Morocco, is being impacted by both climate change and human activity [1]. Monitoring its surface water dynamics becomes essential for effective water management and ecological preservation. However, monitoring such changes over extended periods has presented challenges. Recent advancements in remote sensing and cloud computing, particularly with platforms like Google Earth Engine (GEE) [2], have made continuous monitoring feasible. GEE integrates Landsat data, allowing for more efficient analysis. Multiple approaches for detecting, delineating, and mapping surface water are available in the literature [3,4]. For example, Bijeesh and Narasimhamurthy [4] divide them into four categories: methods based on single bands, methods based on spectral indices, methods based on machine learning, and methods based

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on spectral mixture analysis. To our best knowledge, there has been limited research dedicated to exploring the long-term surface water dynamics in Morocco [5], notably at El Mansour Eddahbi Dam. This study investigates GEE and Landsat images, employing four water indices (MNDWI, EWI, NWI, and AWEI) in conjunction with the random forest-supervised algorithm. The primary goal is to monitor and analyse the changes in surface water at El Mansour Eddahbi Dam from 1984 to 2023. This investigation aims to uncover temporal trends and factors contributing to these observed changes.

2 Materials and Methods

2.1 Study area

The El Mansour Eddahbi Dam is situated in Morocco's southeastern region, within the Drâa-Oued Noun hydraulic water basin (Fig 1). This dam, which was built in 1972, covers 15,000 km² and can hold 428 million m³ of water yearly.

Fig. 1. a) Study area’s location. b) Landsat RGB colour composition for 1984 and 2022.

2.2 Spectral bands and water indices

To detect surface water, all available cloud-free Landsat TM, ETM+ and OLI data from various time periods (1984–1999, 2000–2012, 2013–2023) were employed from the Landsat Level-1 dataset via GEE [2], covering the research area. Specifically, images for 2023 were exclusively acquired from January to July. In this research, a total of 424 images with six spectral bands were collected. Additionally, four spectral water indices, namely modified normalized difference water index (MNDWI), enhanced water index (EWI), new water index (NWI), and automated water extraction index (AWEI) were used. Further information about these indices can be found in [3–5]. Applying these spectral water
indices approach improves image features while reducing the surrounding environmental condition's influence on water, thereby emphasizing water differentiation from other features.

### 2.3 Water extraction algorithm

Based on spectral band and indices, surface water maps were produced for individual years through random forest algorithm \[6\] with a pixel-based approach. Between 416 and 535 sample points were generated for each year and were labeled as water and no-water. The training data was randomly divided into two sets, with 70% used for training and 30% for validation.

### 2.4 Climatic and drought indicators

We chose four climate and drought indicators – precipitation, average temperature, standardized precipitation index (SPI-12) and standardized precipitation evapotranspiration index (SPEI-12) – to analyse their influence on the variations in surface water area. These factors were selected as they are likely to impact changes in the water area \[3,4\]. Climatic data were derived from Drâa-Oued Noun Hydraulic Basin Agency (ABHDON). Subsequently, SPI-12 and SPEI-12 were computed.

### 2.5 Trend and correlations analysis

In this research, the Sen's slope test is applied to analyse time series trends in univariate data, while the Mann-Kendall test is employed for evaluating significance. Moreover, to assess the link between surface water area and climate/drought indicators, Pearson correlation coefficient was used.

### 3 Results and Discussions

With an RF overall accuracy surpassing 98%, the RF model indicates notably high precision in surface water extraction. This demonstrates RF's viability and confirms the dataset's suitability for further spatiotemporal analysis. This finding is consistent with earlier research \[4\] indicating that RF can proficiently extract diverse water body types while reducing noise resulting from shadows.

#### 3.1 Surface water spatial distribution in EME dam

Figure 2 illustrates the EME dam's surface water spatiotemporal distribution obtained by RF over 40 years. Form visual inspection, it is evident that the surface water area exhibits noticeable inter-annual variations. These fluctuations suggest a recurring pattern of expansion and contraction in spatial terms. For instance, in 1984, the total surface water area was 4.22 km², accounting for 0.61 % of the entire studied area. In contrast, by 2023, the surface water area had expanded to 16.11 km² (2.35%). Notably, when compared to the severe drought conditions experienced in 1984, a moderate increase in surface water was observed in 2023.
3.2 Surface water temporal distribution and correlation analysis

The surface water area of the EME Dam exhibited a general decrease during 1984–2023 (as shown in Figure 3a). Nonetheless, this trend is statistically insignificant (with p-value = 0.1518 > 0.05 at a 95% confidence level). Furthermore, it can be observed that the surface water area showed a typical pattern of decrease and increase (Figure 3a-b). Notably, the smallest water area was observed in 1984–1986, averaging 6.38 km$^2$. This was significantly lower than the average from 1984 to 2023 (30.05 km$^2$). These years had a severe drought, as confirmed by [1]. Additionally, surface water area has experienced a downward trend during 1999–2001, 2010–2014, and 2016–2022. For instance, severe drought occurred in 1999, with [7] reporting that the inflow water drastically decreased from 367 Mm$^3$ to 79
Mm³ during the hydrological years 1997/1998 and 1998/1999, respectively. This finding aligns with [5]’s results, which also indicate a water decline in al Massira dam during 1999–2000 and 2014-2021. Nevertheless, between 1988 and 1998, the EME’s dam surface water area varied between 37.12 and 47.04 km². Specifically, the largest area was recorded in 1988 (47.04 km²). In this year, the area experienced a substantial change of about +500% in comparison to 1987, as illustrated in Figure 3c. Conversely, negative change ranged from -42.97% (1999) to -1.06% (1992).

**Fig. 3.** a) Surface water area inter-annual variation during 1983–2023. b) Yearly variations (%) in surface water area relative to the previous year. c) Pearson correlations among surface water area, precipitation, average temperature and drought indices (SPI-12 and SPEI-12).

Pearson correlation analysis indicates that the EME Dam’s water surface area is significantly influenced by various climate-related factors, notably drought indices (Fig 3-c). It has a substantial positive correlation (0.71) with drought indices like SPI-12 and SPEI-12, indicating that it tends to decrease during drier periods. Precipitation has a moderately positive correlation (0.34). Nevertheless, the average temperature shows a weak negative correlation (-0.03), suggesting its limited impact on the water surface area. Obviously, these aforementioned relationships highlight the EME dam’s susceptibility to drought severity, precipitation levels, and to a lesser degree, temperature variations.

### 4 Conclusions

Surface water maps are essential tools for monitoring water resources and understanding climate changes impact. This research examined the yearly spatiotemporal fluctuations in the surface water area of the EME Dam between 1984 and 2023. The analysis utilized all accessible Landsat TM, ETM+, and OLI images on the GEE platform. The RF overall accuracy for extracting the EME Dam's surface water was consistently above 98%. Moreover, spatiotemporal analysis revealed that substantial changes in the EME dam’s surface water have been detected over the last 40 years.
Acknowledgments

We extend our acknowledgment to the Google Earth Engine (GEE) team and the United States Geological Survey (USGS) for providing Landsat imagery. We are grateful to the Drâa-Oued Noun Hydraulic Basin Agency (ABHDON) for providing meteorological data.

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