RESEARCH PAPER

MONITORING OF WATER SURFACE DYNAMICS OF THE SONG HINH HYDROPOWER RESERVIOR (VIETNAM) USING GOOGLE EARTH ENGINE

Quoc Khanh Nguyen[1], Mai Phuong Pham[1*], Trong Nhan Nguyen[2*]
[1]Joint Vietnam - Russia Tropical Science and Technology Research Center, Hanoi, 100000, Vietnam
[2]Faculty of Geodesy, Cartography and Geographic Information, University of Natural Resources and Environment, Ho Chi Minh, 70000, Vietnam
***Corresponding author:** ntnhan@hcmunre.edu.vn
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ABSTRACT. Reservoirs are facing increasing hydrological pressure, making continuous and accurate monitoring of these resources essential for sustainable management. In this study, we utilized a method involving Google Earth Engine (GEE), a platform with strong data processing capabilities for big data, to analyze and interpret satellite images. The Otsu method was applied to automatically determine the threshold value for extracting the water surface of the Song Hinh reservoir using Landsat 5, 8, and 9 satellite imagery, and to assess changes in the reservoir's surface area. The research results indicated that the water surface area of the Song Hinh reservoir initially increased 4.4 times (1999-2000) and then remained relatively stable (2000-2024). However, during the 2000-2015 period, the water surface area experienced minor expansions and contractions, while during the 2015-2024 period, the surface area expanded insignificantly, with less contraction than in the previous period. Additionally, the analysis results of water surface area changes were used to support the development of Earth Engine Apps, also known as WebGIS, as a tool for monitoring surface water changes in the Song Hinh reservoir. In summary, the results obtained in this study are highly useful as a foundation for developing effective monitoring measures and sustainable resource management for the Song Hinh reservoir area.

KEYWORDS: Earth Engine Apps, GEE, Otsu method, water surface dynamic, The Song Hinh

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INTRODUCTION

Natural and artificial reservoirs are essential sources of freshwater for humans and animals, agricultural irrigation, and industrial use. Reservoirs are under increasing hydrological pressure due to rising water demand, climate change, prolonged droughts, and water pollution. Therefore, continuous and accurate monitoring of these resources is necessary to ensure their sustainable management (Bocchino et al. 2023). Traditional ground-based instruments like gauging stations are still frequently used today to measure water levels. The data obtained from these tools are used to estimate the area and volume of reservoirs, as well as their changes over time, by using elevation curves (volume-area-elevation curves) derived from depth and topographic information specific to the reservoir (Tong et al. 2016, Hamoudzadeh et al. 2023). However, this on-site monitoring method has certain limitations, such as difficulties in installing and maintaining gauging stations in remote areas, equipment malfunctions, and the spatial discontinuity of elevation data (Duan and Bastiaanssen 2013; Fuentes et al. 2019). In contrast, the use of remote sensing (RS) technology can significantly reduce monitoring costs and provide regular data, facilitating continuous monitoring of reservoirs with consistent processes worldwide (Valadão et al. 2021).

For this issue, numerous studies have demonstrated that multi-spectral and multi-temporal RS is a highly feasible option, enabling continuous monitoring of reservoir changes (Jagadeesha and Palnitkar 1991; Busker et al. 2019; Yao et al. 2019; Binh Pham-Duc et al. 2023). Although many studies have applied RS in the analysis of long-term change detection (Alesheikh et al. 2007), several limitations arise related to the need for computation and processing of large amounts of satellite imagery, especially when using medium- and high-resolution images (Zhang et al. 2022). To address this issue, Google Earth Engine (GEE) can be used as a cloud computing platform along with advanced machine learning algorithms to analyze satellite images. GEE offers high-performance parallel computing capabilities, massive remote sensing data, geospatial data, and free access while providing a new approach for long-term time-series analysis and large-scale remote sensing analysis (Wang et al. 2021). Based on the development tools for JavaScript or Python algorithms on the web, it not only enables rapid online visualization and RS data analysis but also supports the free development of Apps, also known as WebGIS (Kwong et al. 2022).

As mentioned above, RS can help enable the monitoring of water boundary changes. Many studies have employed different methods for water surface extraction, including the Normalized Difference Water Index (NDWI); however, this index has shown overall poor effectiveness [15] (Xing et al. 2022). In contrast, the Modified Normalized Difference Water Index (MNDWI) has demonstrated better adaptability and stability in distinguishing between water and land areas (Wang et al. 2017; Zhang and Liu 2022; Singh et al. 2015; Vasanthi and Joshitha, 2024), making it a preferred choice over NDWI. Additionally, Green/SWIR and Green/NIR ratios also allow for effective water surface extraction with a threshold value greater than 1 (Ng 2016). However, to clearly separate water and land objects in satellite images, an advanced technique is needed to automatically determine the threshold for water surfaces. For this issue, the Otsu is a useful method that helps optimally determine the threshold value in images (Otsu 1979).

The Otsu method is a widely used thresholding technique for gray-level images, with applications ranging from defect detection to OCR binarization and image pre-processing for historical document searching (Jianzhuang et al., 1991; Ng, 2006; Gupta et al., 2007). The method has been extended to 2D histograms for image segmentation, with techniques such as 2D histogram projection and wavelet transform proposed for threshold correction (Zhang et al., 2008). More research has looked into how the Otsu method compares to other clustering algorithms, like K-means, and found that their objective functions for multilevel thresholding are the same (Liu et al., 2009). Additionally, studies have focused on optimizing the Otsu method for multi-level thresholding using a two-stage optimization approach (Huang et al., 2009). A characteristic analysis of the Otsu threshold has also been conducted, highlighting its applications in various fields (Xu et al., 2011). Some changes have been suggested to the Otsu method to make automatic thresholding work better. These include the valley-emphasis method and a modified two-dimensional segmentation algorithm (Fan et al., 2012; Chen et al., 2012).

The Otsu's method, a popular image thresholding technique in computer vision and image processing, has several limitations that can affect its performance in certain scenarios. One major limitation is the difficulty in segmenting images with objects of complex and irregular geometry, especially those with many edges or inclusions (Ma et al. 2017). This limitations can lead to challenges in accurately detecting and separating different regions within the image. Additionally, the Otsu's method may not perform optimally when faced with images that have varying lighting conditions or noise levels. Despite its limitations, the Otsu's method remains a valuable tool for simple image thresholding tasks. It is known for its simplicity, efficiency, and parameter-free nature, making it a popular choice for many applications (Sha et al. 2016). The Otsu method continues to be a valuable tool in image processing and analysis, with ongoing research focusing on optimization, applications, and improvements to the original algorithm (Liu et al., 2014). OTSU can be applied to threshold vegetation indices such as NDVI (Normalized Difference Vegetation Index). For example, it can differentiate areas with high and low vegetation density (Xu et al., 2020). For soil indices, such as NDSI (Normalized Difference Soil Index) (Härer et al., 2018) or the Brightness Index (BI) (Deng and Zhang, 2021; Kakooei and Baleghi, 2020), OTSU can also be used to separate land regions. In cloud segmentation, OTSU can be employed to distinguish cloud regions in satellite images based on reflected light intensity, often using optical bands with high values in cloud areas. When processing satellite imagery for analyzing air pollution or dust, OTSU can help classify different pollution zones. The method's reliance on a simple histogram is a key limitation. Since OTSU only analyzes the image's histogram, it may not effectively separate indices lacking a clear bimodal distribution.

The Earth Engine Apps (EEapp) created on GEE is a powerful tool for analyzing and monitoring Earth's environment through satellite data. GEE provides a cloud platform that allows users to access, process, and analyze vast amounts of geospatial data efficiently. The EEapp enables researchers, scientists, and nonprofit organizations to track and monitor environmental changes such as climate change, deforestation, water fluctuations, and other natural phenomena. With a diverse data library, including petabytes of historical and current satellite data from sources like NASA, USGS, and ESA, users can easily perform complex analyses without needing to invest in high-tech infrastructure. The application provides powerful programming tools through JavaScript and Python APIs, allowing for the creation of custom maps and visual reports. GEE also supports collaboration and sharing of research results, helping the scientific community and policymakers make data-driven decisions based on accurate and up-to-date information. With its easy access and superior processing power, the EEapp is an indispensable tool for natural resource research and management.

Recent studies have demonstrated the effectiveness of using GEE in monitoring water surface changes. Wang et al. (2021) utilized Landsat 5, 7, and 8 images along with GEE to monitor water surface fluctuations at the Xiaolangdi reservoir, achieving an overall accuracy of 98.86% and a kappa coefficient of 0.96. Xing et al. (2022) used the GEE platform to track changes in the water surface in Shandong Province, China, from 1990 to 2020 using Landsat imagery. The results indicated that it could provide an important application for sustainable water resource management. Recently, GEE has also been applied in Vietnam to monitor water surface fluctuations in various water bodies (Vu Anh Minh et al. 2024; Binh Pham-Duc 2024). This method is considered a tool for effective water resource management in developing countries. It not only automatically detects, monitors, and evaluates water surface fluctuations over space and time for reservoirs but can also be extended to other surface water bodies and coastal lagoons (Condeca et al. 2022). However, in Vietnam, studies applying GEE to monitor water surface changes are still limited, particularly in multi-purpose reservoirs used for irrigation, aquaculture, flood regulation, and power generation. This situation highlights the need for research in these reservoirs.

The Song Hinh Hydropower Reservoir is a hydropower facility located on the Hinh River, a major river in Phu Yen Province, with the dam situated approximately 40 km southwest of Tuy Hoa city. The reservoir plays a crucial economic and environmental role for the local area and neighboring regions. The primary function of the Song Hinh Hydropower Plant is electricity generation with a designed capacity of 70 MW and an average annual output of 357 million kWh, which is integrated into the national grid to meet the economic needs of the population. After power generation, the water (averaging 36.99 m^3/s) provides supply for industrial activities, domestic use, and irrigation for over 19,800 hectares of agricultural land downstream (Le Cong Tuan and Hoang Dinh Trung 2024). Monitoring water surface fluctuations of this important hydropower reservoir is significant for socio-economic development and environmental protection in the southern region of Phú Yên Province. In this study, Landsat 5, 8, and 9 images were collected for the Song Hinh Reservoir area from 1999 to 2024. We used the GEE method, a powerful cloud-based platform for processing large datasets, to analyze and interpret satellite images and applied the Otsu method to automatically determine threshold values for extracting the water surface of the Song Hinh Reservoir. The objectives of this study are (1) to extract the water surface using GEE and Otsu methods; (2) to identify spatial and temporal changes in the water surface area of the Song Hinh Reservoir using GIS software; and (3) to develop Earth Engine Apps as a basis for creating a WEBGIS system to support the management and monitoring of water resources in the reservoir as climate change and human activities increase. The results provide a scientific basis for environmental protection, water resource management, economic activities, and assist policymakers in developing effective strategies for resource management and environmental protection.

MATERIALS AND METHODS

Study area and data

Study area

The Song Hinh Hydropower Reservoir is the largest reservoir in the Hinh River basin of Phu Yen Province (Fig. 1), with a catchment area of 772 km^2. The reservoir has a normal water level of 209 meters, a dead storage level of 196 meters, a dam crest elevation of 215 meters, a total storage capacity of 357 million m^3, and a maximum flood discharge capacity of 6952 m^3/s (Hai et al. 2020). Construction of the reservoir began in 1993, power generation started in 1999, and it was inaugurated in 2001. Its primary functions are to provide water for irrigation, domestic use, and industrial purposes in the Son Giang and Son Thành areas; to supplement water for the Dong Cam irrigation system to ensure irrigation capacity for the summer-autumn crop; and to supply water to the Ban Thach River (Vi 2020). The Song Hinh Reservoir is located in the region with the highest rainfall in Phu Yen Province, with annual precipitation measured between 2200-2400 mm. Rainfall during the four-month rainy season (September-December) accounts for 69-72% of the annual total, and the average annual temperature is approximately 26°C.

Data sources

A GEE platform has been used to collect images, classify, and assess accuracy using machine learning and artificial intelligence algorithms (Tamiminia et al. 2020). This platform provides a powerful and flexible analytical environment for large datasets from Landsat. Accuracy improvement of the images is achieved through machine learning algorithms to ensure accurate results on changes to the Earth's surface. Notably, GEE is an open-source tool that offers computational resources and satellite data for free on a cloud computing platform, thereby reducing costs and benefiting users.

In this study, the images used are surface reflectance images from Landsat 5-TM, 8, and 9-OLI satellites with a spatial resolution of 30 meters, collected to create a comprehensive database for analyzing and extracting the water surface of the Song Hinh Reservoir from 1999

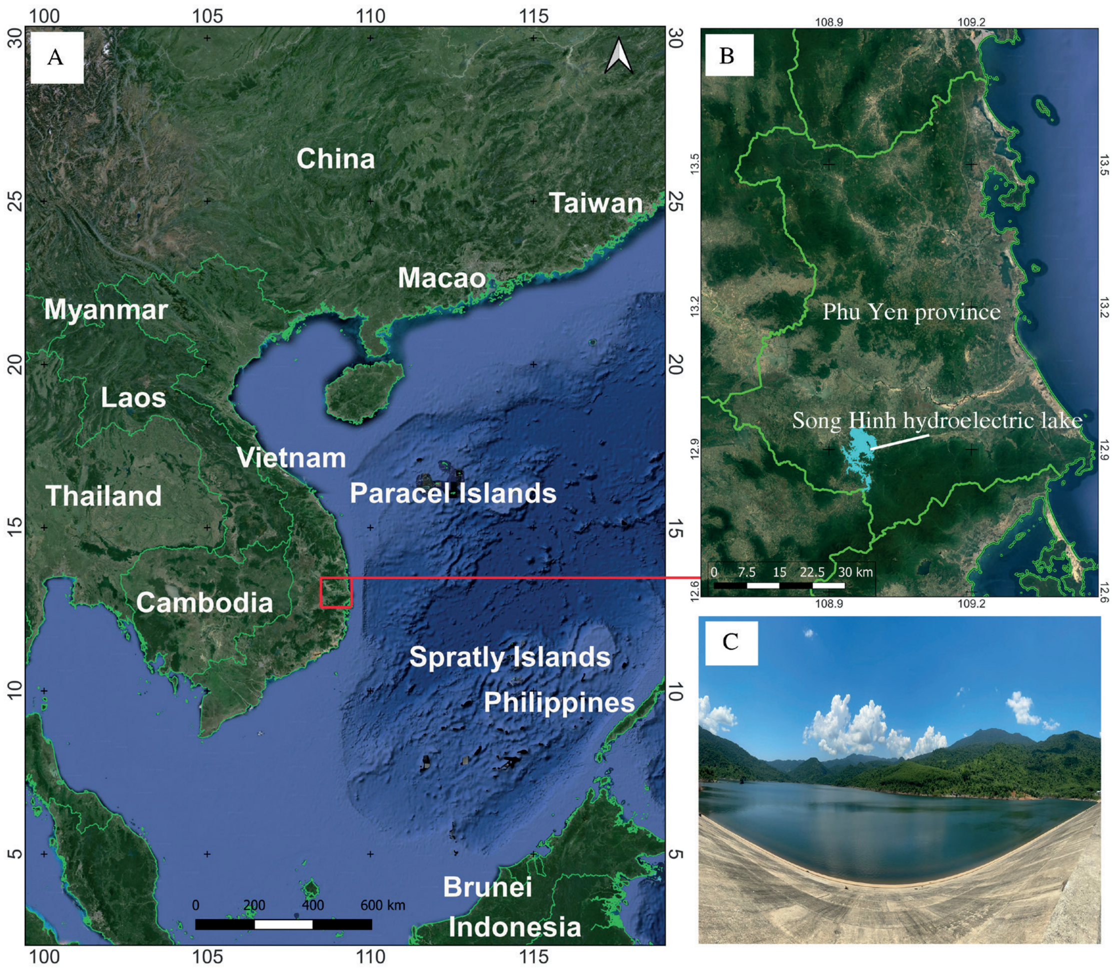

Fig. 1. Study area

to 2024. Table 1 provides detailed information about these image scenes. The collection of reflectance images allows for the removal of cloud-covered areas using the 'pixel qa' band. Image classification was performed for the years 1999, 2000, 2015, and 2024, using scripts and datasets specific to each period.

Image pre-processing

We processed the images by applying a cloud mask layer to each dataset, aiming to create composite images with an acceptable level of cloud cover. This cloud filtering process uses the 'pixel qa' band in the surface reflectance collections to remove clouds and cloud shadows, resulting in cloud-free RGB composites (Markert et al. 2018). For further analysis of the study area, we used the boundary of the Song Hinh Reservoir to crop the images, retaining only the portion within this area. This format ensures that the processed image data focuses on the Song Hinh Reservoir area and is not affected by external factors outside the study area.

METHODS

The Otsu's Method

The Otsu's Method is named after a Japanese researcher (Nobuyuki Otsu), who proposed the idea of assuming the gray levels of the target object and the background object in an image to construct a histogram with Gaussian distribution and equal variances (Otsu 1979). Thus, the Otsu's method is a technique for determining a threshold based on the gray level histogram with binomial distribution. However, this method is ineffective when the pixel variance between the object to be extracted and the background object in the image is too large or when the histogram is constructed as a unimodal distribution with a single peak (Ng 2016; Truong and Kim 2018). According to the Otsu's method, the threshold *k** is determined (Eq. 1) so that the two classes (C1 and C2) in the image have significant differences, meaning that the variance is maximized (Pritam and Prasenjit 2010).

$$k^* = argmax_{0 \le k \le L-1}\left\{\omega_1(k)\mu_1^2(k) + \omega_2(k)\mu_2^2(k)\right\} \quad (1)$$

where C1 is the class containing gray level values in the range [0,…, k]; C2 is the class containing gray level values in the range [k+1,…, L-1]; ω_1 and ω_2 are the probabilities of the two classes in the image, calculated according to Eq. 2:

$$\omega_1(k) = \sum_{i=1}^{k} P_i \, và \, \omega_2(k) \sum_{i=k+1}^{L-1} P_i \quad (2)$$

μ_1 and μ_2 are the mean values calculated using Eq. 3:

$$\mu_1(k) = \sum_{i=0}^{k} \frac{i \times p_i}{\omega_1(k)} \, và \, \mu_2(k) \sum_{i=k+1}^{L-1} \frac{i \times p_i}{\omega_2(k)} \quad (3)$$

After determining the threshold *k**, thresholding is performed to create a binary image. Pixels with gray levels greater than the threshold *k** are assigned a value of 1, while those with gray levels less than *k** are assigned a value of 0 (Eq. 4).

$$g(x,y) = \begin{cases} 1 f(x,y) > k^* \\ 0 f(x,y) < k^* \end{cases} \quad (4)$$

where *g(x,y)* is the function representing the gray level value at point *(x, y)* on the output image; *f(x,y)* is the function representing the gray level value at point *(x, y)* on the input image.

Using the JavaScript programming language to extract water surfaces and analyze spatial changes over time to determine the changes in the water surface of the Song Hinh Reservoir, and this is done on the GEE platform. Additionally, GEE supports designing WebGIS interfaces or Earth Engine Apps and developing interactive functionalities with the maps.

RESULTS

Water surface extraction for research stages

In this study, we used the near-infrared (NIR) band to construct a histogram by applying the Otsu's method on the NIR band of optical images from Landsat 5, 8, and 9, with a DN (Digital Number) threshold value to separate water surfaces, as water is fully absorbed in the infrared region. Water has a strong absorption characteristic in the NIR region, so water bodies in NIR images typically appear as areas with very low DN values. The Otsu's method works based on the image's histogram, which is a frequency distribution chart of DN values in the image. Otsu searches for the optimal segmentation threshold by optimizing the ratio between intra-class variance and inter-class variance, aiming to minimize the total variance within each class (Fig. 2, 3).

Using the Otsu's method to find the optimal DN threshold. This method automatically calculates the threshold so that the total variance within the classes is minimized. The threshold separates the image into two parts: one representing water (low DN values) and the other representing land and other objects (high DN values). Then, the DN threshold found by the Otsu's method is used to create a segmentation mask. DN values lower than the threshold are assigned as water, while DN values higher than the threshold are assigned as land or other objects. This method eliminates the need for manual threshold selection, saving time and reducing subjective errors. It aligns with the spectral characteristics of water in the NIR region, allowing for accurate water surface extraction. In water resource research and management, the use of the Otsu's method on the NIR band of Landsat images can help with the following: (1) monitoring water level changes: detecting and tracking changes in water bodies over time; (2) land cover classification: assisting in the classification

Table 1. Information on the satellite images used

Satellite images	ID Images	Time
Landsat 5	LANDSAT/LT05/C02/T1_L2/LT05_123051_19990319	1999-03-19
Landsat 5	LANDSAT/LT05/C02/T1_L2/LT05_123051_20000508	2000-05-08
Landsat 8	LANDSAT/LC08/C02/T1_L2/LC08_124051_20150407	2015-04-07
Landsat 9	LANDSAT/LC09/C02/T1_L2/LC09_123051_20240416	2024-04-16

and mapping of water and land areas; (3) natural resource management: supporting the management and protection of water resources. The Otsu method applied to the NIR band of Landsat images is a powerful, simple, and effective tool for separating water surfaces from other objects, thanks to water's strong absorption characteristics in the NIR region.

Spatiotemporal variations of the water surface in the Song Hinh Reservoir

Based on the results in Figs. 4 and 5, the water surface fluctuations across the study periods are evident. In the 1999-2000 period, the water surface of the Song Hinh Reservoir expanded significantly, with an area of approximately 39.28 hectares. There was no significant reduction in the water surface area during this period. The 2000-2015 period saw major stability, with an unchanged water surface area accounting for about 45.11 hectares. However, during this period, a small reduction in water surface area was observed (2.93 hectares), while the expanded area was 1.32 hectares. In the 2015-2024 period, the unchanged water surface continued to dominate, covering around 44.98 hectares. The reduction in water surface area was significantly smaller compared to previous periods, around 1.44 hectares, and the expanded water surface area was very minimal, only 0.14 hectares. Overall, the 1999-2000 period experienced the most substantial expansion of the water surface in the Song Hinh Reservoir, while in the 2000-2015 period, most of the water surface remained unchanged, with minor expansion and contraction. Data from the 2015-2024 period show the reservoir's water surface was relatively stable, with the shrinkage of the water surface trending lower than in previous periods, and expansion being very limited. These data reflect the spatiotemporal variations in the water surface over time, indicating environmental impacts and other factors affecting water resources.

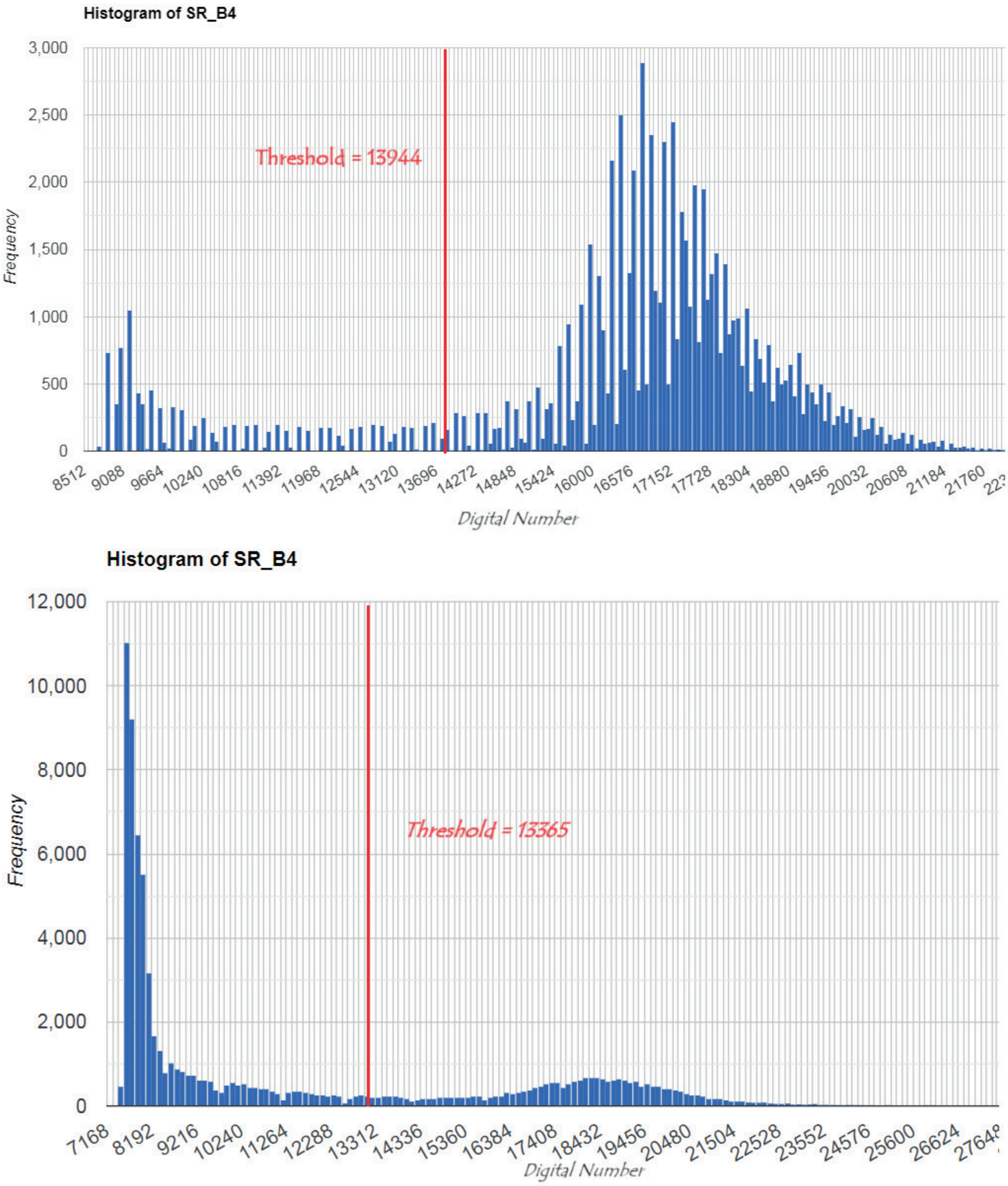

Fig. 2. DN threshold values for 1999 and 2000

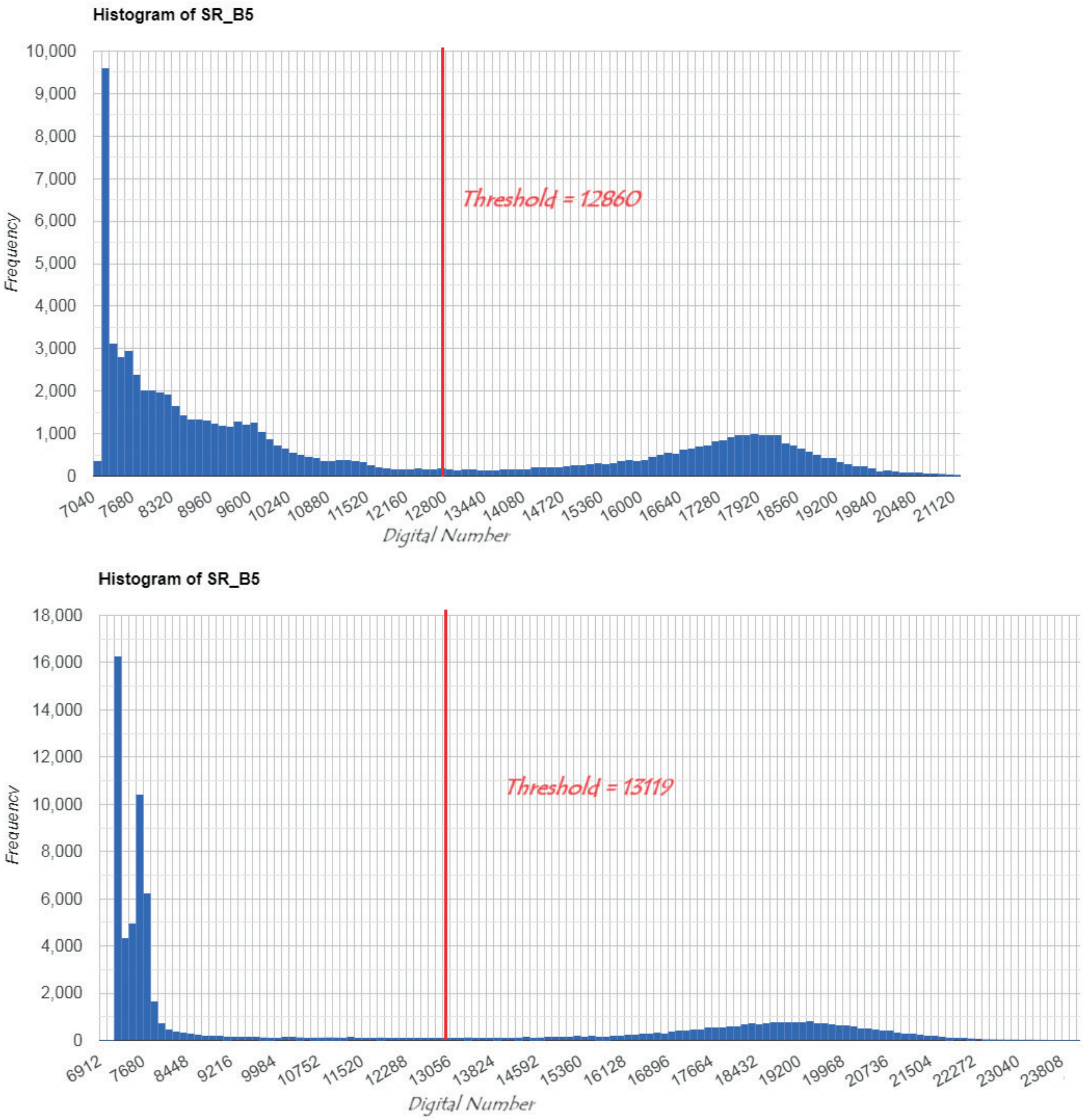

Fig. 3. DN threshold values for 2015 and 2024

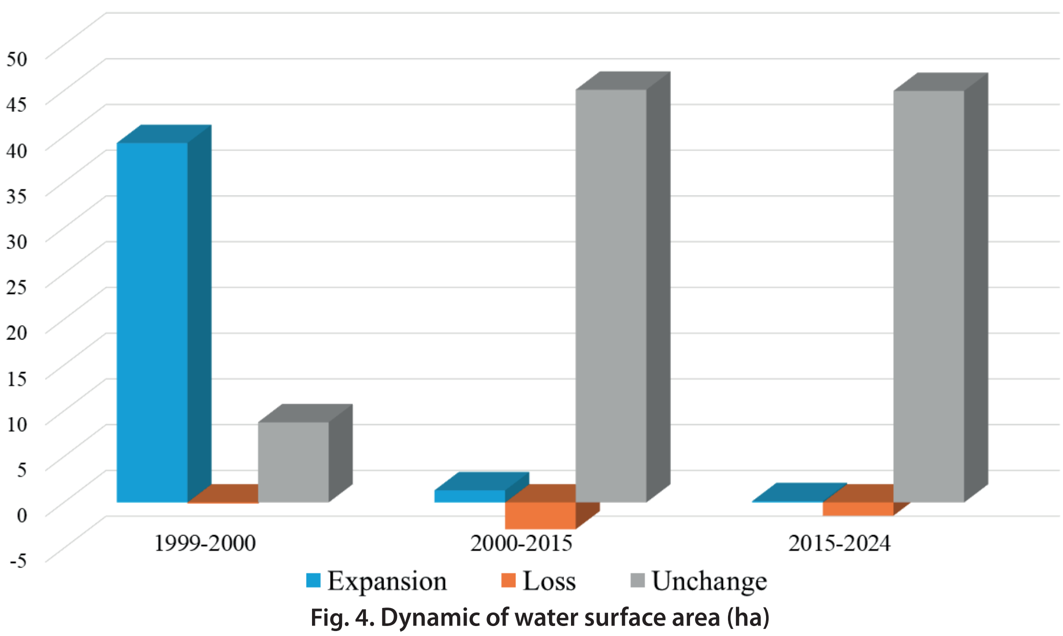

Fig. 4. Dynamic of water surface area (ha)

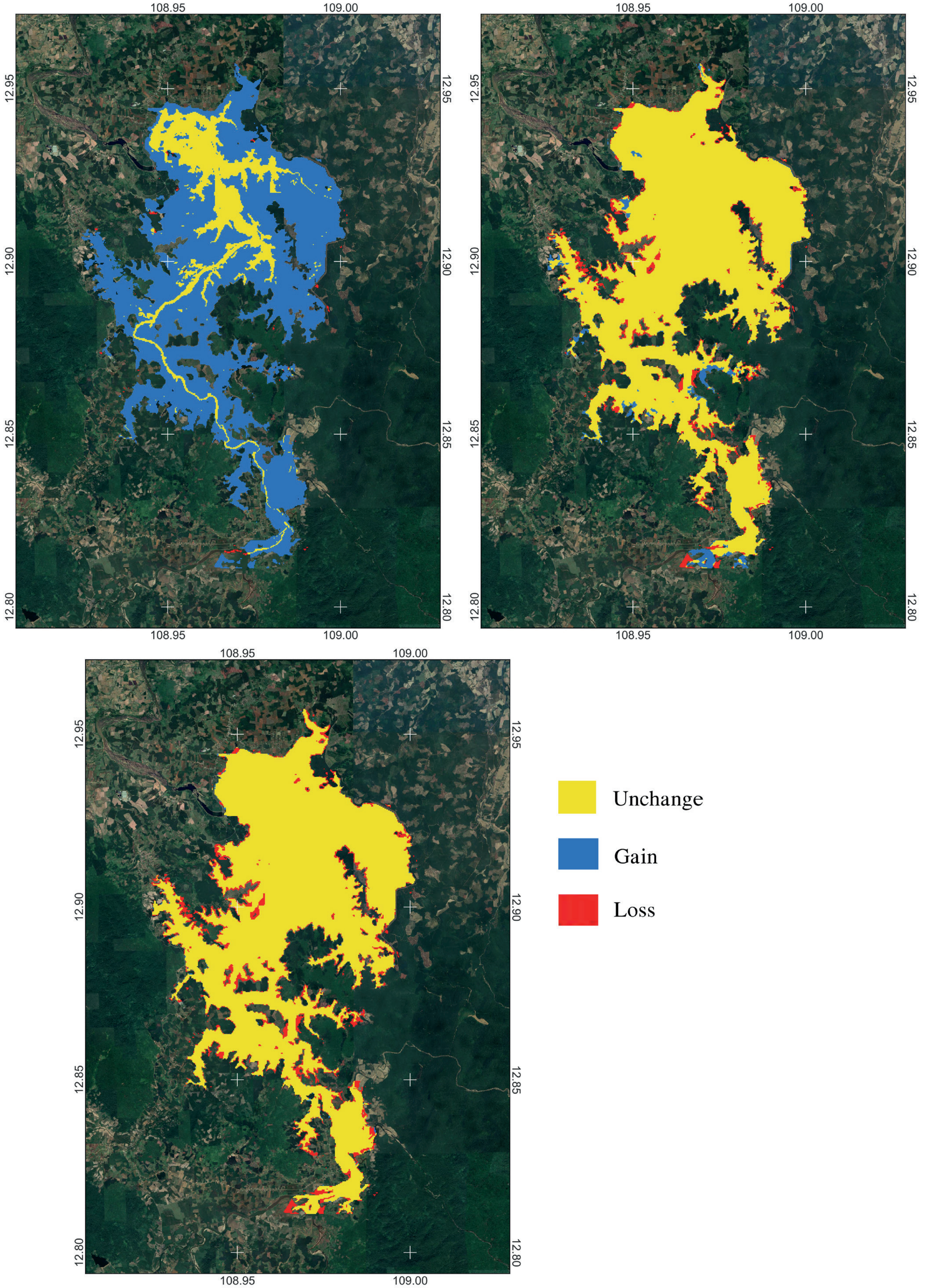

Fig. 5. Map of water surface area changes in the Song Hinh Reservoir: (a) 1999 - 2000; (b) 2000 - 2015; and (c) 2015 – 2024

Developing Earth Engine Apps

Through the analysis of water surface variations and utilizing the functions available on the GEE platform, we have developed an online Earth Engine App to allow users to monitor and analyze trends in water surface area over time (Fig. 6). This enables the assessment of the impacts of climate change, drought, or human activities on the reservoir. In addition to zooming in and out of the map to display different areas, users can interact with the app by creating time-series charts, which could potentially extend the application for water quality monitoring. Regular monitoring helps in the early detection of signs of depletion, pollution, or other relevant issues, enabling timely and effective water resource management (de Albuquerque Teixeira et al., 2024). GEE's capability to process and analyze satellite data in real-time and historically provides managers with a comprehensive and accurate overview of reservoir conditions. Data from GEE supports decisions for water resource management, such as water regulation and management for agriculture and industry. GEE can analyze water quality indicators such as chlorophyll levels and turbidity, allowing for early detection of pollution (Sherjah et al., 2023). For reservoirs near the coast, monitoring saltwater intrusion is crucial to protect freshwater ecosystems and drinking water sources. Researchers can use GEE data to conduct studies on hydrology, ecology, and climate change (VanDeWeghe et al., 2022). GEE data can also be used to develop predictive models for future water level changes in reservoirs (Lu and Sun, 2023). Using GEE in educational and outreach programs helps raise community awareness about the importance of protecting and managing water resources. Local communities can engage in monitoring and protecting the reservoir through user-friendly GEE applications (Boothroyd, 2021).

Limitations of the study

Selection of Satellite Images

Our study focuses on evaluating the changes in the water surface area of the Song Hinh Reservoir before and after the construction of the hydropower dam. This approach was guided by the unique characteristics of the region, where water surface fluctuations are primarily influenced by dam construction and reservoir operations rather than natural hydrological variations. To capture this transformation, we deliberately selected four satellite images representing distinct developmental stages of the reservoir. However, this selection presents certain limitations. By relying on a limited number of images, our analysis may not fully capture short-term variations in water extent due to seasonal or interannual hydrological dynamics. Furthermore, while we acknowledge the influence of precipitation patterns, inflow/outflow dynamics, and water level fluctuations, these factors were not explicitly incorporated into our analysis. Expanding the dataset to include a broader temporal range and integrating additional hydrological variables could provide a more comprehensive assessment of the reservoir's long-term dynamics.

Connection Between Water Level and Surface Boundary Estimation

While we recognize the importance of linking water level measurements with estimates of water surface area, our study primarily utilized Google Earth Engine (GEE) as a practical tool for detecting spatial changes in water boundaries. The efficiency of GEE in extracting and processing spatial data makes it a valuable resource for water resource monitoring. However, the absence of historical design data correlating water levels with surface areas for the Song Hinh Reservoir limited our ability to

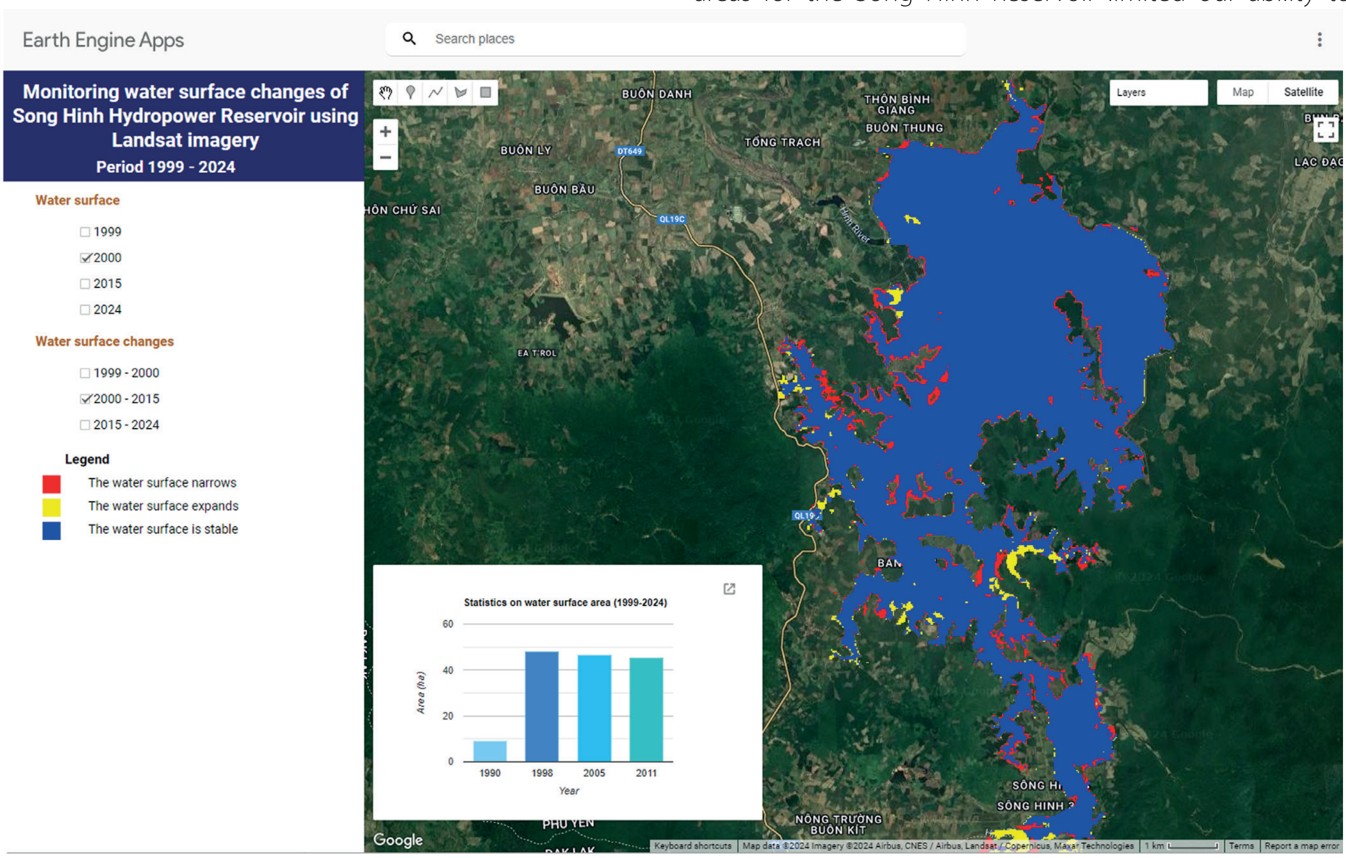

Fig. 6. Screenshot of the online application developed on GEE for monitoring water surface changes in the Song Hinh Reservoir from 1999 to 2024

conduct a direct quantitative analysis of this relationship. Although our methodology demonstrates the adaptability of GEE for spatial data analysis, future studies could benefit from incorporating water level records, hydrological modeling, or additional in situ measurements. Such an approach would enable a more precise assessment of reservoir storage capacity and operational changes over time.

Emphasis on the Potential of Google Earth Engine

One of the key contributions of our study is to highlight the applicability of GEE for analyzing water surface dynamics, especially in data-scarce regions. GEE's ability to integrate and process large datasets efficiently makes it a powerful tool for reservoir monitoring. However, our study primarily focused on spatial analysis without incorporating advanced hydrological simulations or validation against ground-based observations. Additionally, while GEE-generated outputs can be seamlessly integrated into WebGIS platforms, their accuracy depends on the quality of input satellite data and the classification algorithms used. Future research should explore the integration of GEE with machine learning approaches, multi-source satellite data fusion, and hydrodynamic modeling to enhance the accuracy and applicability of water resource assessments.

CONCLUSIONS

In this study, the Otsu method was used to extract water surface area in the NIR band of Landsat 5, 8, and 9 optical images with DN threshold values. The research results precisely clarified the historical periods when water surface area was affected, leading to an increase in water surface area during 1999-2000 and subsequent contraction (adjustment) in the following years. By the 2015-2024 period, the water surface area had stabilized with negligible increases and decreases. Major past water surface fluctuations were caused by hydroelectric dam construction activities, which expanded the water surface area to 39.28 hectares (approximately 4.4 times the area before 1999). The assessment results greatly contributed to the development of Earth Engine Apps for monitoring the Song Hinh Reservoir's water surface, aiding in the management, protection, and research of water resources while enhancing community awareness and participation in environmental protection. In summary, this study demonstrates that the GEE cloud computing platform can develop a web application with effective, comprehensive, and cost-efficient capabilities, providing rapid information to improve water resource monitoring.

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