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Remote sensing applications for reservoir water level monitoring, sustainable water surface management, and environmental risks in Quang Nam province, Vietnam

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ABSTRACT

Monitoring surface water provides vital information in water management; however, limited data is a fundamental challenge for most developing countries, such as Vietnam. Based on advanced remote sensing technologies, the authors proposed a methodology to process satellite images and use their outcomes to extract surface water in water resource management of Quang Nam province. Results of the proposed study show good agreement with *in situ* measurement data when the obtained Overall Accuracy and Kappa Coefficient were greater than 90% and 0.99, respectively. Three potential applications based on the surface water results are selected to discuss sustainable water management in Quang Nam province. Firstly, reservoir operating processes can be examined, enhanced, and even developed through long-term extracted water levels, which are the interpolation results between the extracted surface water area and the water level–area–volume curve. Secondly, the long-term morphological change for the Truong Giang river case between 1990 and 2019 can also be detected from the Water Frequency Index performance and provided additional information regarding permanent and seasonal water changes. Lastly, the flood inundation extent was extracted and separated from permanent water to assess the damage of the Mirinae typhoon on 2 November 2009 in terms of population and crop aspects.

Key words: Quang Nam province, remote sensing, satellite images, surface water, water indices, water management

HIGHLIGHTS

- Excellent performance of extractions for surface water features, i.e., reservoirs and rivers, from water indices and satellite images.
- Reservoir's dynamic assessment for water level monitoring and operations.
- Long-term morphological changes in the Truong Giang river and its adjacent areas for sustainable management.
- Flood extent detection for flood hazard and risk assessment.

1. INTRODUCTION

In recent years, issues related to water resources are spreading out, especially floods and inadequate water. Biswas (1979) stated that developing countries suffer severe water problems, which promotes local authorities and researchers to approach sustainable water management. Surface water is one of the major features in water resources, providing vital information in water management, and this feature's detection can be irreplaceable management strategies for both developed and developing nations (Karima 2014). However, the surface water dataset is mainly collected from manual methods, which consume considerable amounts of time and money (Sarp & Ozcelik 2017).

From reliable performance and regularly updated data sources, remote sensing technologies based on satellite images have become popular methods to observe and manage natural resources over past decades (Song *et al.* 2008; Wu *et al.* 2008; Shirazi *et al.* 2017; Favretto 2018). Numerous remote sensing-based methodologies of surface water extraction from the optical remote sensing imagery were developed (Sharma *et al.* 1989; Cheema & Bastiaanssen 2017; Herndon *et al.* 2020), and the common principle is to compare the lower reflectance of water with other land cover types (Frazier & Page 2009). The two most commonly-used satellite images are from the Landsat series of the National Aeronautics and Space Administration (NASA) and Sentinel of the European Space Agency (ESA) (Huang *et al.* 2018). Spatial resolutions of these satellite images are divided into three categories: high (<5 m), medium (5 ÷ 200 m), and course low (>200 m) resolutions (Van der

Woerd & Wernand 2018). Images having medium spatial resolution can detect all types of surface water, and several methodologies to delineate surface water from these images have been developed over decades (Jiang *et al.* 2014). Huang *et al.* (2018) showed three common methods to extract surface water: spectral bands, classification, and water indices, where water indices have higher accuracy and more efficient processes. The two most popular water indices are the Normal Difference Water Index (NDWI) and the modified Normal Difference Water Index (mNDWI) (Acharya *et al.* 2018). By using visible green light and reflected Near-Infrared (NIR) radiation, NDWI can define and improve water detection in satellite images (McFeeter 1996). Xu (2006) concluded that the Middle-Infrared band (MIR) is less sensitive to sediment concentration and other optical constituents within the surface water, and he replaced the NIR band to develop the formula of mNDWI to obtain a better performance than NDWI (Xu 2006). Other indices, i.e., AWEI (Feyisa *et al.* 2014) and WI2015 (Fisher *et al.* 2016), can also provide adequate results. In addition, Xu (2018) had introduced the Water Frequency Index (WFI) to create the annual water distribution map by stacking all satellite images in a year, where the water and non-water pixels had been classified. The outcome of mentioned methods can become vital information in various water resource fields, from surface water dynamics, wetland management, and climate models to agricultural suitability (Sun *et al.* 2012).

In this study, temporal and spatial data of surface water in Quang Nam province from 1990 to 2020 were obtained by processing satellite images and calculating two water indices, i.e., NDWI and mNDWI. The outcomes provide beneficial information for sustainable water management in reservoir operation, long-term river morphological changes, and flood extent and damages in Quang Nam province.

2. STUDY AREA AND DATA

2.1. Study area

Quang Nam province has diverse water resources, consisting of an extensive river network, various reservoirs, and a long coastline (Figure 1). Two major river systems, namely Vu Gia–Thu Bon (VG-TB) and Tam Ky, enter the East Vietnam Sea through Cua Dai, Cua Lo, and Ky Ha estuaries. The Truong Giang river connects VG-TB and Tam Ky river systems and plays a crucial role in local economic development, especially aquaculture and agriculture (Duy *et al.* 2017). With different storage capacities from low (0.2 Mm^3) to high (100 Mm^3), 40 reservoirs bring enormous benefits for citizens. Several hydroelectric plants, e.g., Song Tranh 2 (190 MW) and A Vuong (210 MW), were constructed to provide large storage capacity and electric supply. There are also many irrigation reservoirs, e.g., Giang reservoir, which provides irrigating water and a beautiful landscape for the province.

However, Quang Nam province witnessed massive typhoons and floods over the past decades, resulting in significant property losses. Specifically, Mirinae typhoon struck Quang Nam on 2 November 2009, and caused massive damage to the local economy, in particular agriculture.

2.2. Data

Two types of data collected to serve this study's purpose are satellite images and *in situ* data.

Satellite images were downloaded from the United States Geological Survey (USGS) portal, which collects, monitors, analyses information about natural resources, and provides users with valuable datasets and snapshots. The images of Landsat and Sentinel-2 satellites are used to identify water distribution over large areas. Landsat satellite sensors, including TM (Thematic Mapper), ETM+ (Enhanced Thematic Mapper Plus), and OLI/TIR (Operational Land Imager and Thermal Infrared Scanner), have a moderate spatial resolution of 30 m and a 16-day revisit time (Jiang *et al.* 2014). Whereas Sentinel-2 can offer a higher accurate resolution (10 m) of the spatial snapshots of Earth's surface (Lefebvre *et al.* 2019) and has little influence from shadows and built-up area (Zhang *et al.* 2019). All collected images, which must have a cloud-covered percentage under 50%, were used for the surface water extraction from 1990 to 2019 (Table 1 and Figure 2).

Reference data, including Google Earth Pro™ images and *in situ* measurements, were used to evaluate surface water bodies' performance. Images from Google Earth Pro™, a virtual globe that represents the Earth in three dimensions with high resolution ranging from 15 m to 15 cm (Farr *et al.* 2007), were captured to verify the accuracy of the extracted surface water mask. For the *in situ* data, the cross-sections of the VG-TB river system and Global Positioning System (GPS) points within the Truong Giang river were collected from topographical survey campaigns in 2017 and on 7 June 2020. Besides, measured water levels in reservoirs were collected from the Vietnam Electricity Corporation (https://hochuathuydien.evn.com.vn), which can be used to interpolate the surface water area from the water level–area–capacity curve of the reservoirs.

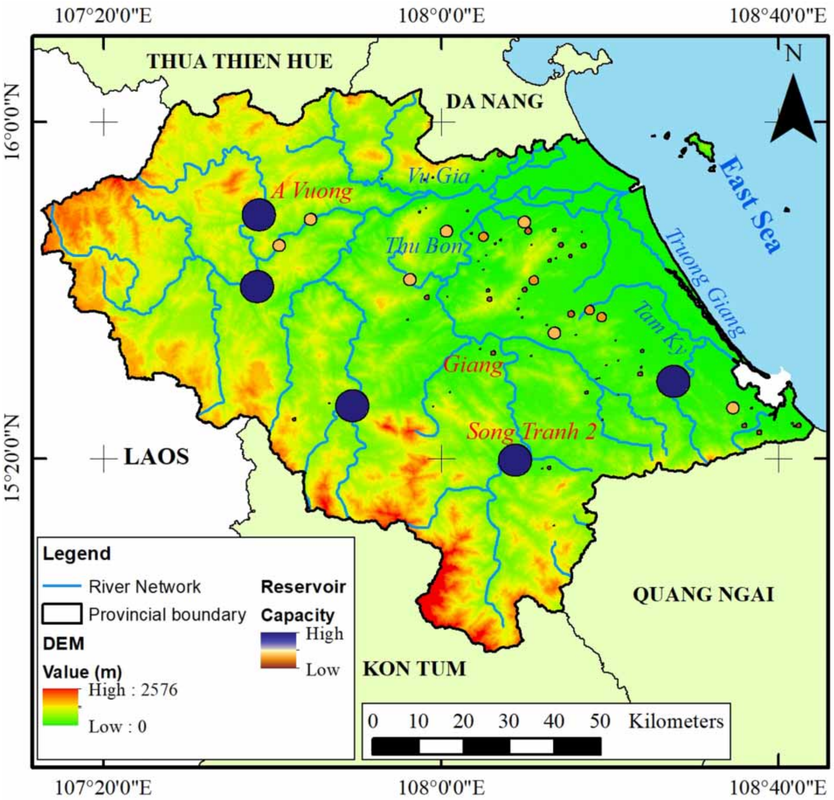
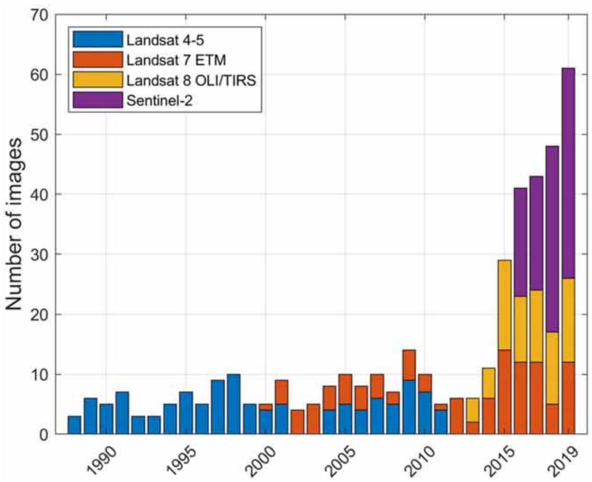


Figure 1 | Quang Nam province and its diverse water resources.

Table 1 | Satellite image attributes (European Space Agency n.d.; National Aeronautics & Space Administration n.d.)

Satellite image	Number of bands	Spatial resolution (m)	Revisit time (days)	Type of sensors	Current status
Landsat 4–5	7	30–120	16	MSS and TM	Ended on 2013
Landsat 7	8	15–60	16	ETM +	Operational
Landsat 8	11	30–100	16	OLI and TIRS	Operational
Sentinel-2	13	10–60	10	MSI	Operational



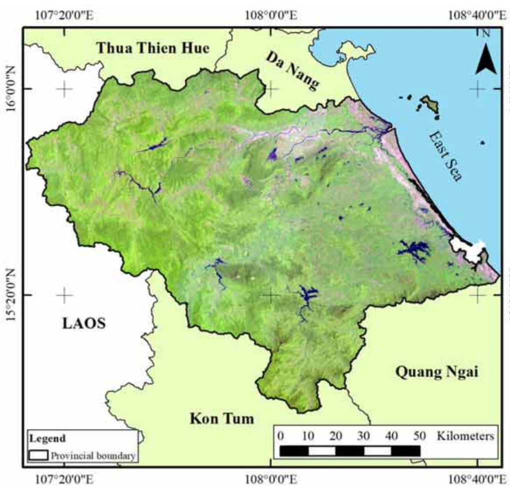


Figure 2 | Annual distribution of satellite images (left) and natural-color image (right) of Quang Nam province.

3. METHODOLOGY

The Landsat and Sentinel images were downloaded from the USGS portal, and several steps to preprocess these images were performed before water indices calculation. Then, the geoinformatic tools of ArcGIS software (© Esri) were used to determine each pixel's value. Finally, the surface water was discretized from other land covers by choosing a suitable reflecting water value. The adopted methodology to detect and extract surface water bodies can be summarized in four steps (see Figure 3).

3.1. Preprocess satellite images

The study area covers both mountainous and delta regions; thus, removing distortion parts in the satellite images is essential. The 'Top of Atmospheric' reflectance was calculated to compensate for the variation in image acquisition under different Sun illumination conditions. The conversion of digital number (DN) values to reflectance played a vital role in quantitative comparison in multi-temporal images (Lu *et al.* 2008), and thus, these values were adjusted due to seasonal conditions and then converted into the Top of Atmospheric Reflectance (Singh & Singh 2017).

3.2. Calculate water indices

McFeeter (1996) firstly proposed NDWI to map and highlight water distribution in satellite images by using the Green and NIR bands as the parameters in the formula:

$$\mathrm{NDWI} = (\mathrm{Green} - \mathrm{NIR})/(\mathrm{Green} + \mathrm{NIR}) \tag{1}$$

Non-water features, i.e., soil and vegetation, were reduced in NDWI models when the low reflectance of the NIR band is suppressed and the green wavelength maximizes the reflectance of water at the same time (McFeeter 1996). However, this index cannot separate constructed land from surface water and therefore tends to overestimate the water distribution (Xu 2006).

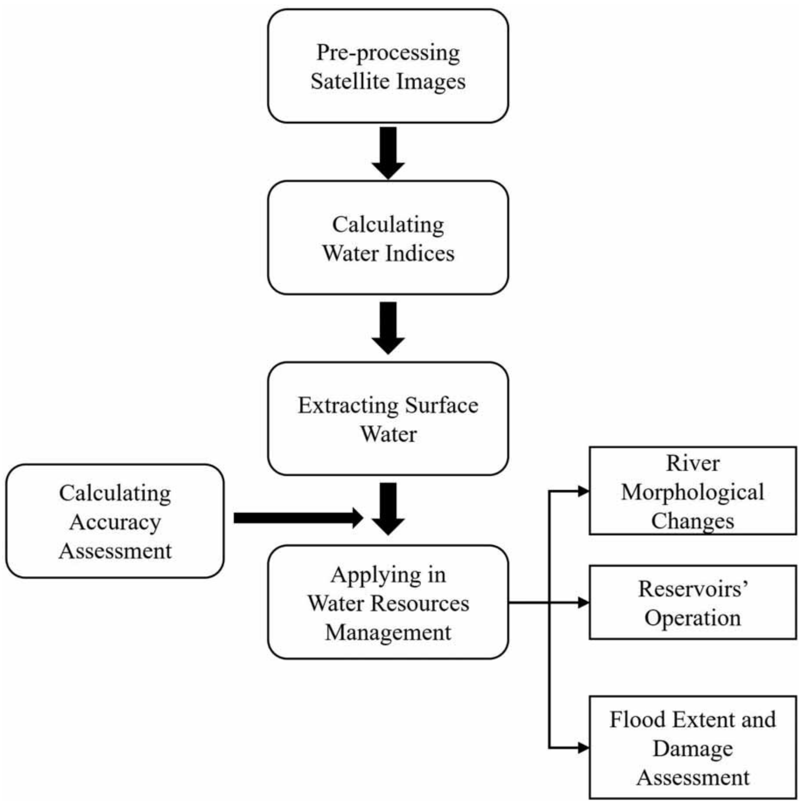


Figure 3 | Overall methodology.

Xu (2006) had modified the formula of NDWI by using the MIR band, instead of the NIR band, to propose the modified Normal Different Water Index (mNDWI). The result of mNDWI can reduce and remove built-up land noise and showed better performance in extracting surface water compared with NDWI models. The mNDWI formula is expressed as:

$$\mathrm{mNDWI} = (\mathrm{Green}-\mathrm{MIR})/(\mathrm{Green} + \mathrm{MIR}) \tag{2}$$

Equations (1) and (2) will be expressed differently for each satellite. For Landsat images, both NDWI and mNDWI can be applied because Green, NIR, and MIR bands have the same solution of 30 m (Rokni *et al.* 2014). Meanwhile, NDWI was adopted for Sentinel-2 images because the resolution of Green and NIR bands is 10 m, while other bands have the resolution ranging from 20 to 60 m (Galar *et al.* 2019).

3.3. Extract surface water

The values of water indices range from −1 to 1. To extract surface water areas, the suitable threshold values need to be determined for detecting pixels reflecting water. According to the reflecting characteristics of water, Xu (2006) indicated that the positive values of NDWI and mNDWI could distinguish surface water from other land cover types. The total amount of pixels having positive values reflects the extent of surface water. After applying receiver operator characteristic curves, he concluded zero value as the optimal threshold to classify land and water features. Other studies, however, suggested that adjusting the threshold could achieve a better result of surface water extraction (Ji *et al.* 2009). Automatically thresholding the same surface water groups for time series would be impossible, and thus, for several cases, manual thresholding is essential (Huang *et al.* 2018).

The scope of this study also includes long-term investigation of annual or seasonal surface water, which requires representative surface water from a vast data range for analysis. Thus, the WFI (Equation (3)), introduced by Xu (2018), was used to highlight locations where water appears most frequently before the annual land–water classification maps being created:

$$\mathrm{WFI} = N_{\mathrm{water}}/(N_{\mathrm{water}} + N_{\mathrm{land}}) \tag{3}$$

In this formula, N_{water} and N_{land} denote the number of pixels that were observed as water and land within 1 year, respectively. By adopting WFI from the results of NDWI and mNDWI, the authors determined the high-occurrence water pixel from the water indices results during a specific time, e.g., annual or seasonal scales, then extracted the representative surface water in the following sections.

3.4. Calculate accuracy assessment

The accuracy assessment is conducted to evaluate the performance of the proposed methodology. In this study, the Overall Accuracy (OA) and Kappa Coefficient (KC), calculated through Equations (4) and (5), were adopted to evaluate the accuracy of the extraction results. The OA presents the probability from 0 to 100% of sites having the corrected results comparing with the total reference sites (Alberg *et al.* 2004). Meanwhile, the KC is a measurement of inter-rater reliability for qualitative terms, which shows agreement for computed results (Thompson & Walter 1988).

$$\mathrm{Overall\,Accuracy} = (\mathrm{TP} + \mathrm{TN})/T \times 100\% \tag{4}$$

$$\mathrm{Kappa\,Coefficient} = \frac{(\mathrm{TP}+\mathrm{TN}) - ((\mathrm{TP}+\mathrm{FP}) \times (\mathrm{TP}+\mathrm{FN}) + (\mathrm{FN}+\mathrm{TN}) \times (\mathrm{FP}+\mathrm{TN}))}{1 - ((\mathrm{TP}+\mathrm{FP}) \times (\mathrm{TP}+\mathrm{FN}) + (\mathrm{FN}+\mathrm{TN}) \times (\mathrm{FP}+\mathrm{TN}))} \tag{5}$$

where TP (True Positive) and TN (True Negative) represent, respectively, water and non-water pixels/points that match with the reference sites, while FP (False Positive) and FN (False Negative) refer to those pixels/points that discrepant with the reference sites. The sum of TP and FP is equivalent to that of TN and FN, which equals the total pixels/points (T) for the assessment. When OA approaches 100% and KC nearly equals 1, the extraction performance can be considered almost perfect (Liu *et al.* 2007).

Based on the extracted surface water at two temporal scales, i.e., instantaneous and annual, the authors adopted three remote sensing applications in water management for Quang Nam province, which were illustrated in more detail in the next section.

4. RESULTS

Figure 4 shows the performance of NDVI and mNDVI indices in extracting surface water of Quang Nam province using Landsat 8 OLI/TIRs image on 17 May 2018. Noticeably, a slight difference between the extracted water distribution using two indices can be seen, similar to a study by Herndon *et al.* (2020).

To evaluate the proposed methods' performance, we compared surface water extraction with reference sites, i.e., *in situ* measurements and Google Earth images, and assessed water distribution accuracy through the OA and KP coefficients. Two considered surface water features were rivers and reservoirs, and feature attributions, e.g., length and surface area, were differentiated to obtain an overall evaluation.

4.1. Accuracy assessment of river network extraction

River cross-sections are represented by points with specific attributes such as coordinates and elevation. Longitudinal thalweg profiles (which trace along the deepest part of riverbeds) from the survey campaign were used as verification data for the extracted VG-TB river network from the satellite images in 2017 (Figure 5). Because of the significant large catchment, these profiles were collected separately during the campaign and survey time instead of collecting exact dates that were estimated. Thus, the annual land–water classification map was generated from 43 satellite images captured in 2017 using WFI then verified using 900 surveyed thalweg points. More than 850 points, accounting for 94.5% of all points, were located within the extracted surface water.

Further evaluation was focused on the Truong Giang river, one of the largest and most important river branches in Quang Nam. The representative annual surface water of the Truong Giang river was compared with its surveyed cross-sections (yellow dots in Figure 6), giving the OA of more than 91% and KC of 0.99.

More interestingly, the extraction performance showed even greater accuracy when comparing with the reference sites on the same day. 90 GPS points (yellow points) along the Truong Giang river, measured on 7 June 2020, located perfectly within the extracted surface water from Lansat 8 OLI/TIR image on the same day (Figure 7).

The three above assessments show good agreement between surface water of rivers extracted from satellite images and *in situ* measurement. Thus, with the necessity for a wide range and regularly updated sources in research, the authors developed an application to detect river morphological changes, which will be illustrated in detail in Section 5.2.

4.2. Accuracy assessment of reservoir extraction

This section focuses on accessing reservoirs' dynamics from the proposed surface water extraction techniques. Two reservoirs with significant area differences, Giang (0.58 km^2) and Song Tranh 2 (20.93 km^2), were taken into this assessment. Their surface water bodies (delineated with the white boundaries in Figure 8) were detected and extracted from the Sentinel-2 image on 9 March 2019. By visually comparing with captured images from Google Earth Pro™ on the same day, similar patterns

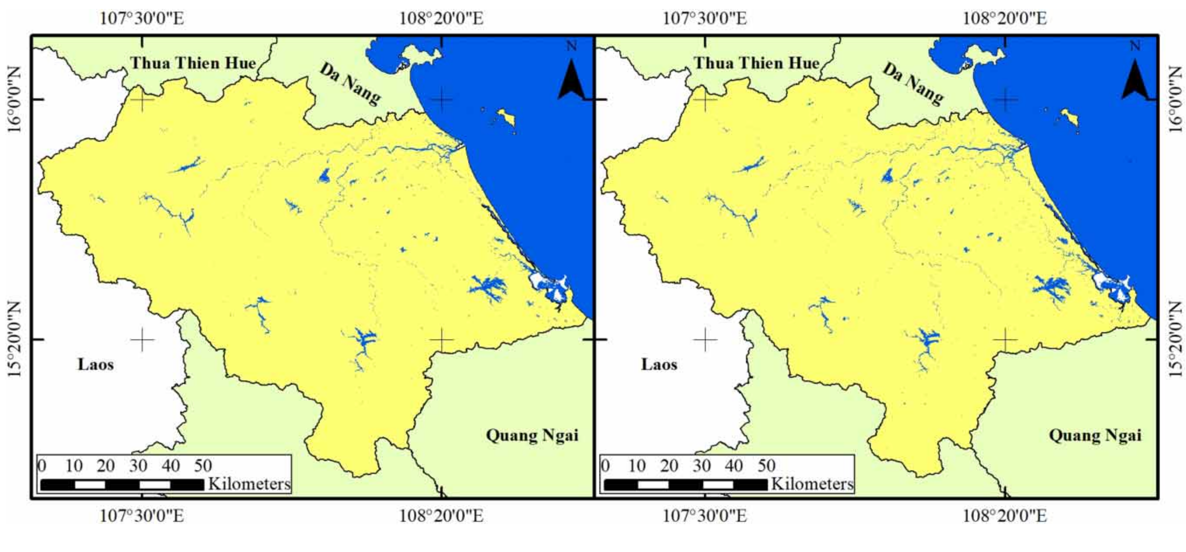


Figure 4 | Water extraction results using NDWI (left panel) and mNDWI (right panel) indices in Quang Nam province.

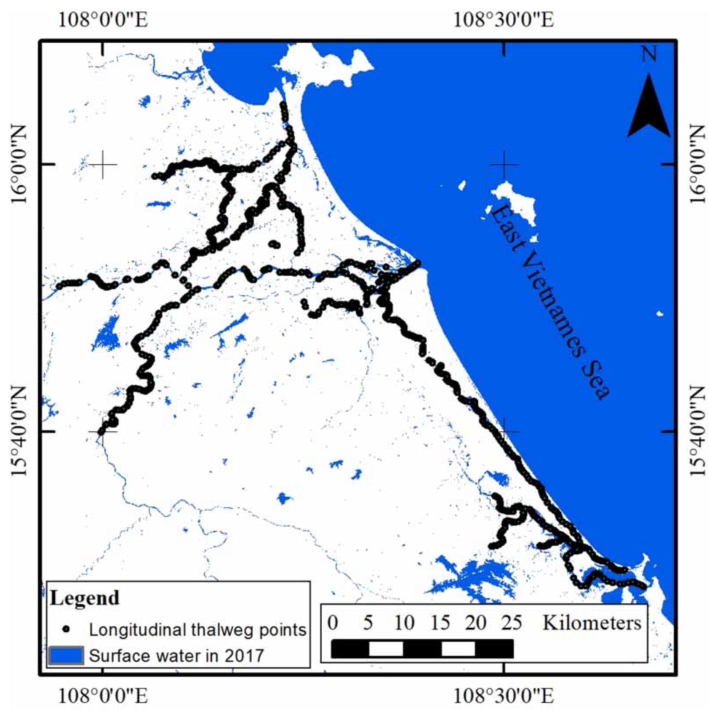


Figure 5 | Verification of extracted river network using surveyed thalweg points.

between the extracted features and the captured images can be observed easily. Remarkably, at the location of the dams or edges of reservoirs in Google Earth, the white boundaries were quite linear (in the figure insets).

Similar to the river network case, the OA and KC values were also adopted to assess the accuracy of the results. More precisely, 1,000 sampling points in the Google Earth referenced image include 500 points within the water body and the others in land cover. The OA values were 96.53 and 99.4% in Giang and Song Tranh 2 reservoirs, respectively, as shown in Table 2. The corresponding KC values were 0.92 and 0.95. These showed excellent agreements between the generated water bodies of the reservoirs and the Google Earth image. The minor errors of extraction may come from the commission of water pixels located around the edges of reservoirs. The unsatisfactory Giang reservoir performance can come from mixed pixels, e.g., water or bare land (Liu *et al.* 2020). There is a common issue for all small water bodies extraction when they usually have a complex morphology, leading to the confusion between water and other features around the water extent's boundaries (Li *et al.* 2013).

The proposed methodology in this study can be an alternative for determining the surface water of reservoirs in addition to measured data through the high value of accuracy assessment and visual inspection. Enormous benefits for reservoir management can be obtained, which will be described in Section 5.1.

5. REMOTE SENSING APPLICATIONS FOR WATER MANAGEMENT IN QUANG NAM PROVINCE BY DETECTING SURFACE WATER FROM SATELLITE IMAGES

Detecting and monitoring surface water can yield vital information about the environment, climate, and humans and become the essential basis for policy and decision-making processes. If water distributions are mapped in temporal and spatial scales, their dynamics can be determined (Acharya *et al.* 2019), and water management fields can take enormous advantages from them (Cheema & Bastiaanssen 2017). However, not all countries, especially the developing ones, have enough resources to develop and synchronize these maps for all regions (Cordery *et al.* 2007). Vietnamese managers are still facing some common shortcomings, mostly a lack of observed data in long-term periods (at annual or seasonal scales) for investigation. This section proposed new methods to apply in water resources management of Quang Nam province, including managing reservoir operation, detecting river morphological changes, and detecting flood extent based on extract surface water results in the above sections.

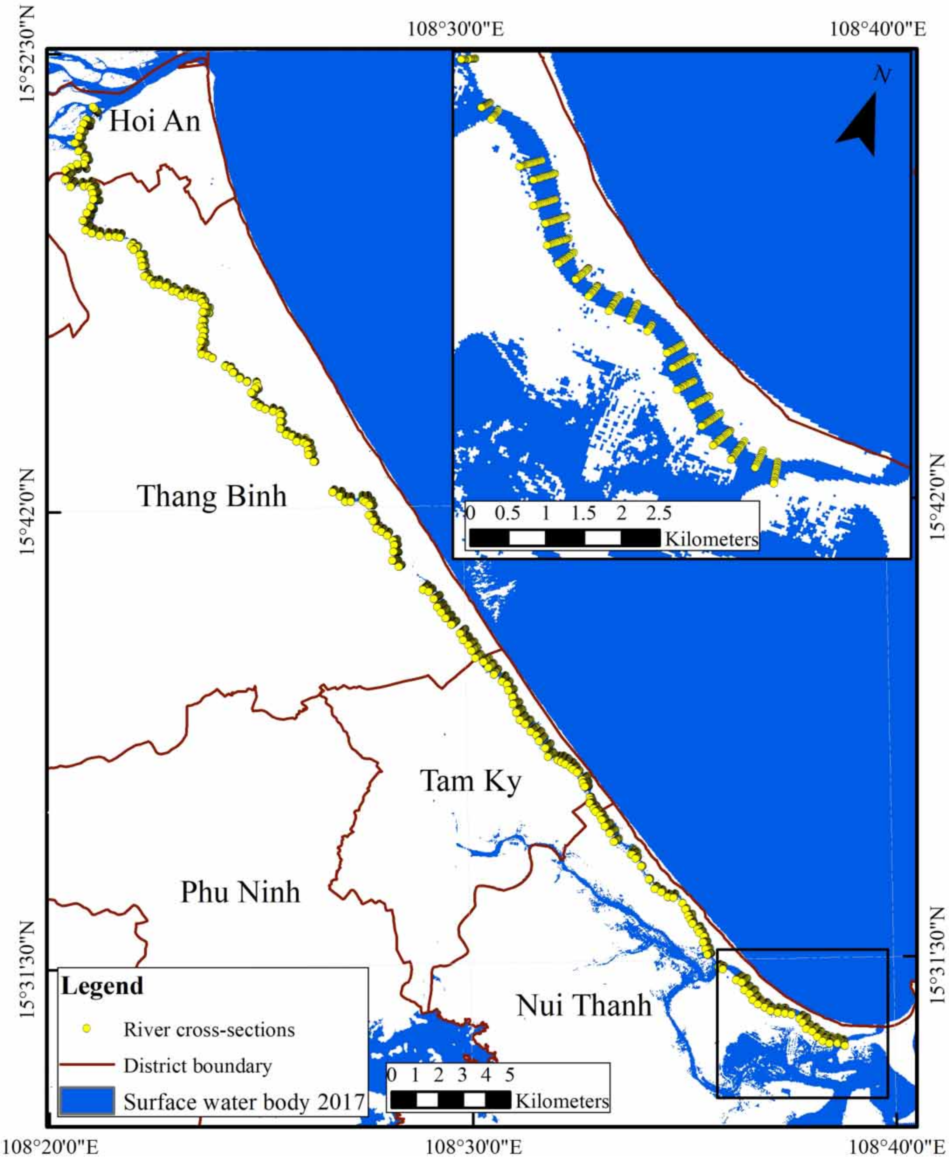


Figure 6 | Verification of extracted surface water of the Truong Giang river and *in situ* measurements. Please refer to the online version of this paper to see this figure in color: https://doi.org/10.2166/wcc.2021.347.

5.1. Reservoir operation management

Reservoir management includes allocating available water for different sectors, water shortage mitigation, and water usage optimization (Hamilton 2015). One of the principal techniques in reservoir management is storage zoning. The reservoirs' horizontal planes are divided into different zones at specific elevations, and the operators regulate water levels within these elevations based on current situations and demands (Jain & Singh 2003). At gauge stations, the operators record water level values several times per day; however, not all reservoirs have equipped these stations. In many developing countries, including Vietnam, numerous reservoirs have not developed operation rules, which hinders management processes and optimal operations. Thanks to remote sensing technology-based satellite images, water levels in reservoirs can be determined from extracted surface water. In this study, the authors assessed A Vuong reservoir's water dynamic by calculating the surface water area from 30 satellite images. Hence, the water level in the corresponding days can be estimated from the water level–area–capacity curve and compared with the *in situ* data.

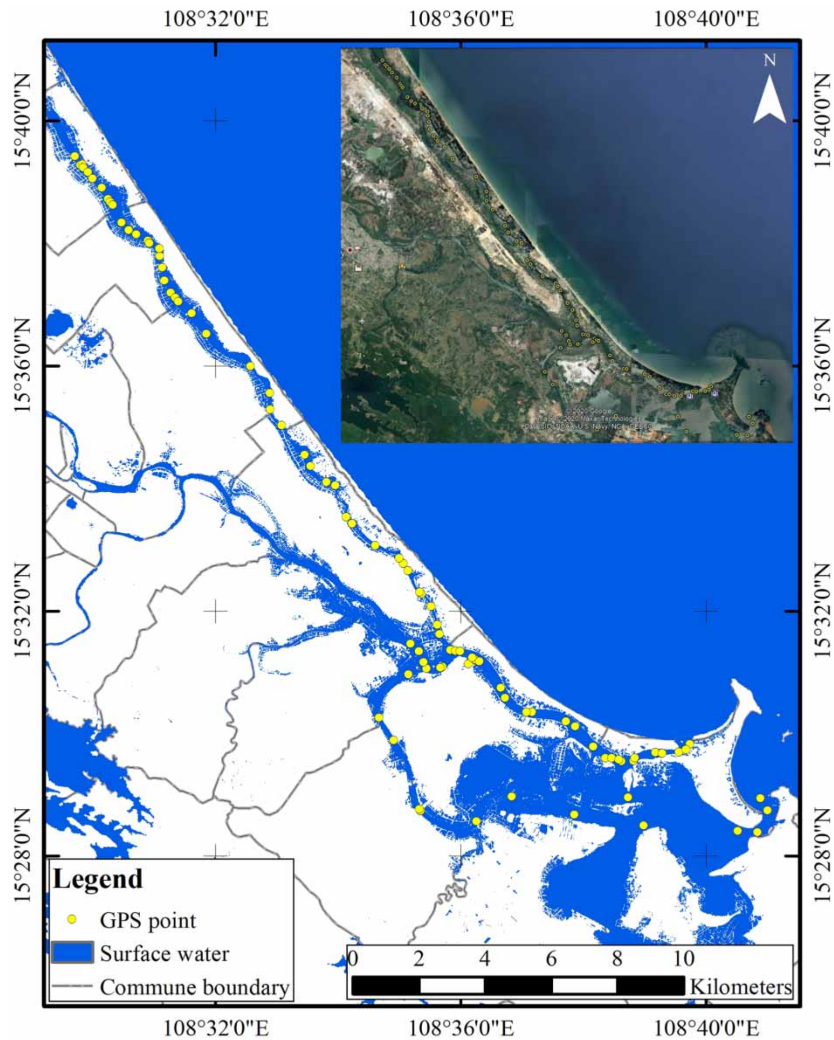


Figure 7 | Verification of extracted river network and measured GPS points on 7 June 2020.

Figure 9 shows A Vuong reservoir's extracted surface water at two different times. On 20 August 2015, when the water level plummeted nearly dead water range (342.34 m), the extracted area was 4.57 km^2. The significant differences in the area (about 4.22 km^2) can be illustrated clearly by comparing the extraction on 20 February 2017, when the water level was 379.96 m and the surface water area was 8.79 km^2. This result shows the promising abilities of proposed water body extraction techniques in surface water change detection between specified time intervals.

Figure 10 represents the extracted area values (green dots) and observed water level. The extracted water variation results are felled between the water level–area curve of A Vuong reservoir at all water level stages, i.e., dead, normal, and flood control. The results showed that the day with higher water levels witnessed a more considerable surface water extent, which corresponded to the relationship pattern in Figure 10.

Based on the relationship curve in Figure 10, the value of water level, area, or capacity can be interpolated if one characteristic is known. In Figure 11, the extracted water level values from satellite images were compared with the observed ones, giving a correlation coefficient (R^2) of 0.984. The water level trajectory also shows good agreement between extracted and observed values since both values have similar trends. For instance, on 5 September 2015, the observed water level declined under the dead water level, which was 339.9 m, and the result from the extraction was 338.71 m. More noticeably, 2015 saw severe drought, salinity, and most water from reservoirs was gathered to irrigate and prevent salt intrusion (Quang Nam People Committee 2016). It can be explained that both observed and extracted water level values on this day were under the dead water level.

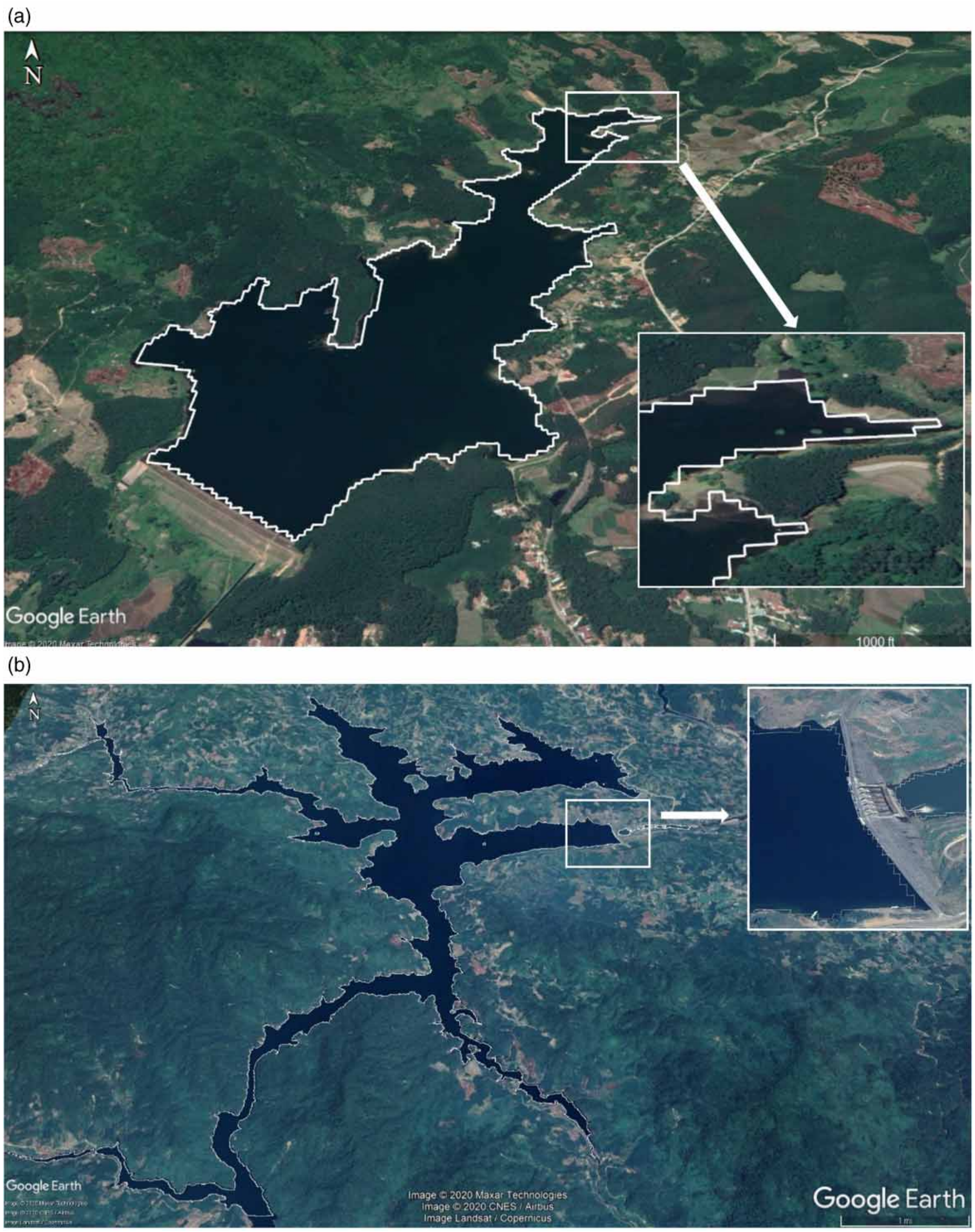


Figure 8 | Validation for Giang (a) and Song Tranh 2 (b) reservoirs.

Table 2 | Accuracy assessment analyses for Giang and Song Tranh 2 reservoirs

Reservoir	Error in area	Overall Accuracy	Kappa Coefficient
Giang	8.62%	96.53%	0.92
Song Tranh 2	4.29%	99.4%	0.95

To conclude, the proposed methodology proves the capabilities of processed satellite images and adopted water indices in analyzing, quantifying, and mapping reservoirs' surface water. Thus, enormous benefits could be achieved in reservoir operation management. For reservoirs with operating rule curves already developed, the operating process can be examined, and

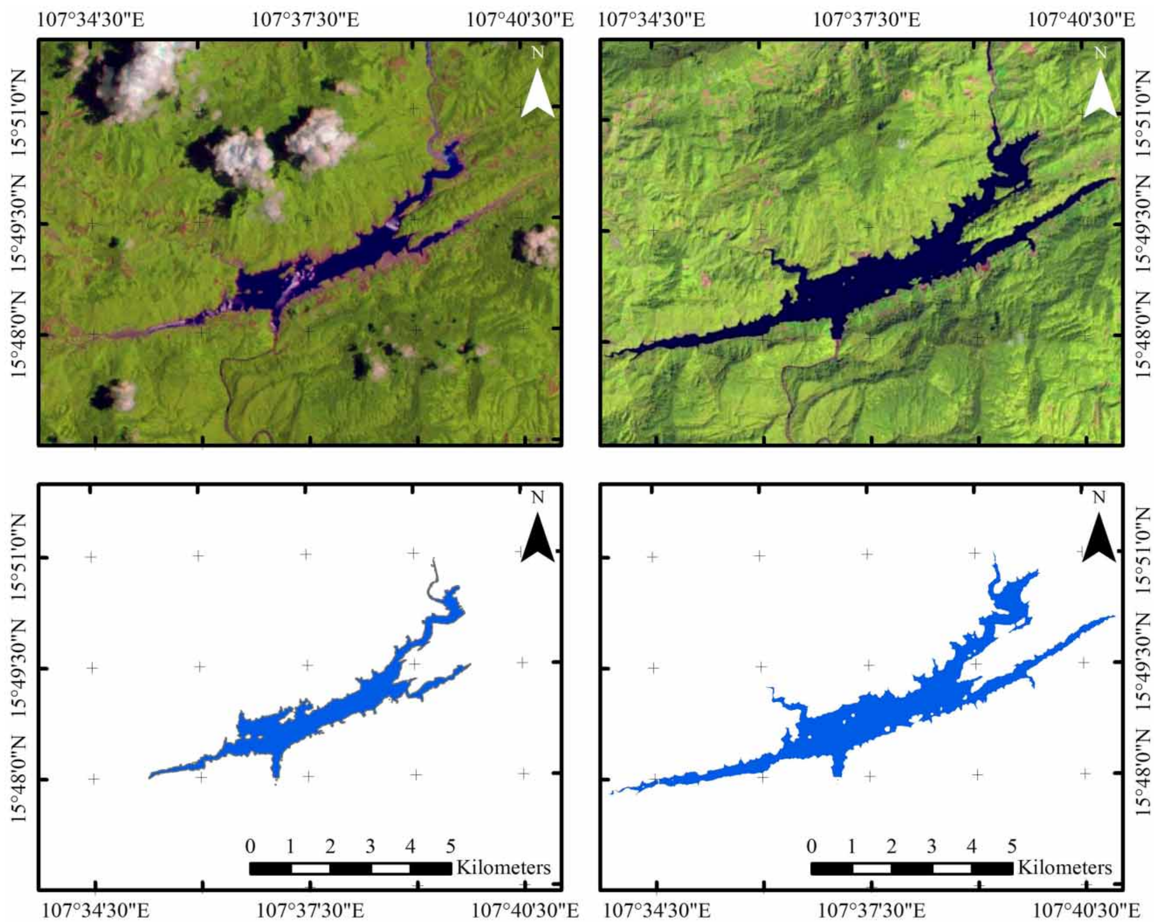


Figure 9 | Natural look image and surface water of A Vuong reservoir at 20 August 2015 (left) and 20 February 2017 (right).

the rule curve's accuracy can be enhanced (Hiep *et al.* 2019). In addition to monitoring the long-term spatial distribution of surface water through satellite images, the proposed techniques can monitor water level, quantify reservoir storage and assess sedimentation, which are prominent issues during reservoir operations (Pandey *et al.* 2016). For reservoirs without rule curves, outcomes of the proposed method could be an essential input to develop this curve and an alternative basis for operators to make future decisions.

5.2. Detection of surface water dynamic over periods

Surface water changes over time due to natural or human impacts (Huang *et al.* 2018). Understanding these changes, also known as river dynamics, can offer optimal solutions to address severe issues such as drought, floods, and water shortages (Tulbure *et al.* 2016). Recently, surface water mapping is a simple and effective method to classify land and water covers, which can be applied widely in water management (Kumar & Reshmidevi 2013). With data covering a wide range of space and time, remote sensing applications become effective tools for detecting surface water dynamics (Sharma *et al.* 1989) and developing land–water cover maps on a time scale.

The present study analyzed surface water dynamics over the last three decades of the Truong Giang river and its adjacent areas, located in four districts: Duy Xuyen, Thang Binh, Tam Ky, and Nui Thanh of Quang Nam province (Figure 12). This river experiences a considerable morphological change due to human impacts (Duy *et al.* 2017). The authors developed annual land–water classification maps of the Truong Giang river and its adjacent areas by adopting the WFI for 30 years. Changes between different periods can be identified easily by overlapping and comparing surface water extraction maps. For instance, two new reservoirs (yellow rectangular in Figure 12) in Thang Binh and Nui Thanh districts were detected in 1990–2005. This period also witnessed a significant morphological change along the Truong Giang river, and several specific locations, particularly at the Ben Da bridge (Figure 13). In reality, the alluvial fans around this bridge cause

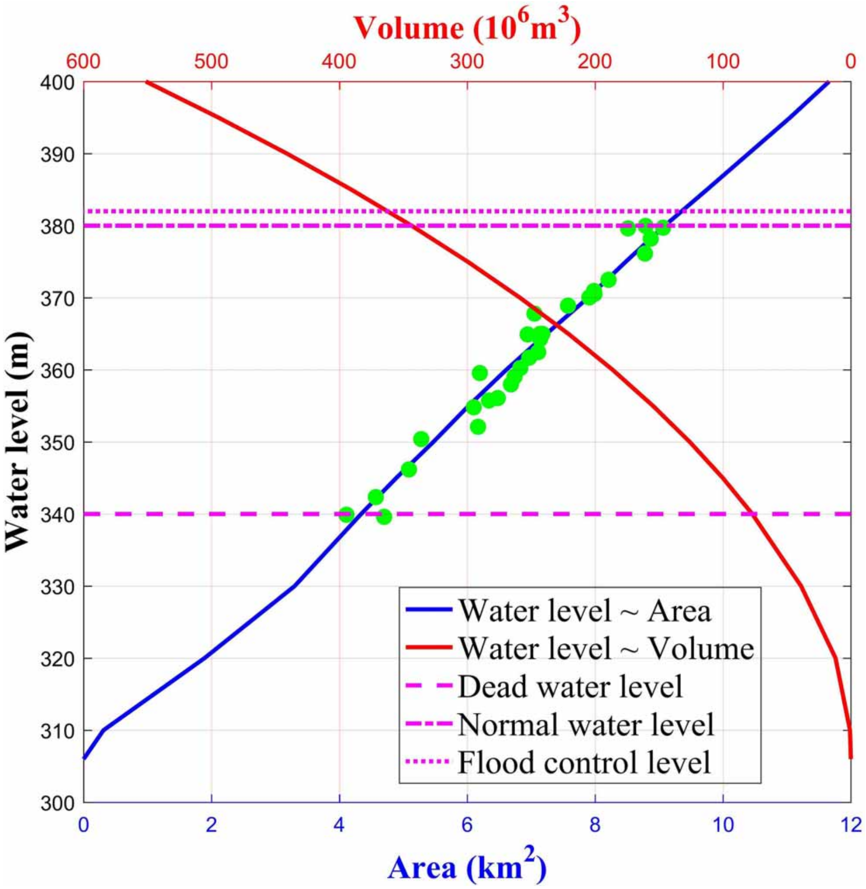


Figure 10 | Water level–area–capacity curve of A Vuong Reservoir (Source: EVN). Please refer to the online version of this paper to see this figure in color: https://doi.org/10.2166/wcc.2021.347.

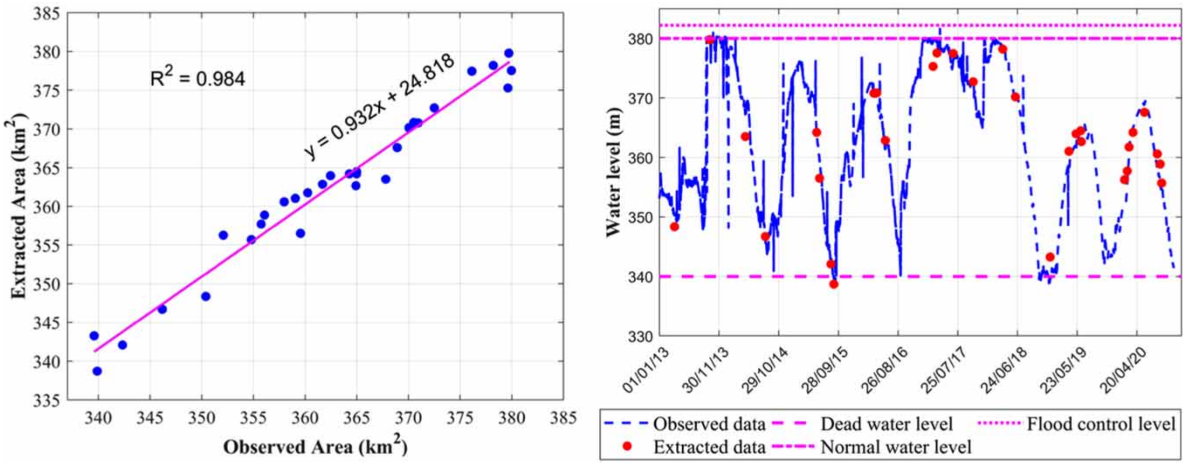


Figure 11 | Scatter plots of 'observed' versus extracted water levels (left panel) and water level trajectory (right panel) of A Vuong reservoir.

sedimentation and meandering, which leads to suddenly abrupt flow and long-term morphological dynamics in the surrounding area (Vietnam Academy for Water Resources 2018).

Moreover, from the annual representative surface water, the authors also determined the fluctuation pattern in the Truong Giang river by calculating its extracted area and then compared it to the statistical data of annual aquaculture productivity

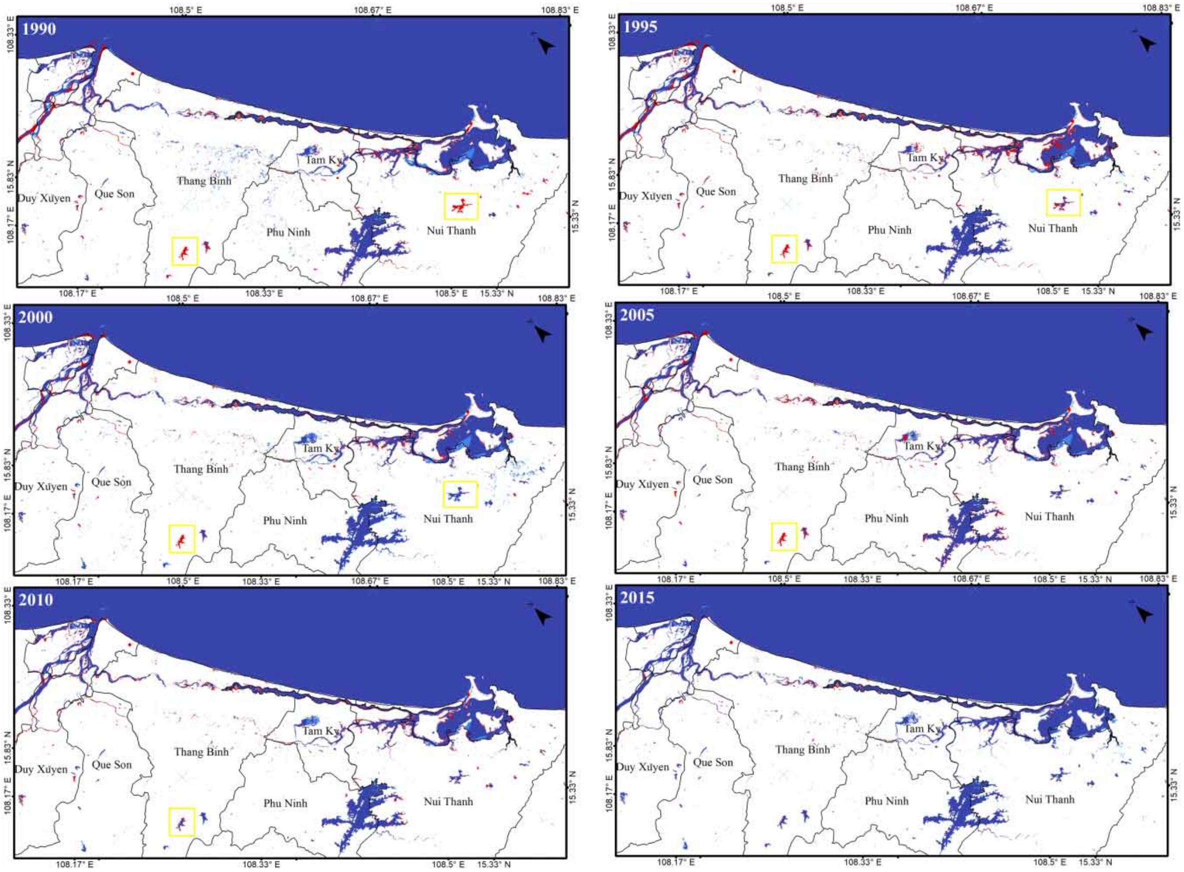


Figure 12 | Changes in surface water bodies of the Truong Giang river and its adjacent areas from 1990 to 2015 (blue) comparing with 2019 (red). Please refer to the online version of this paper to see this figure in color: https://doi.org/10.2166/wcc.2021.347.

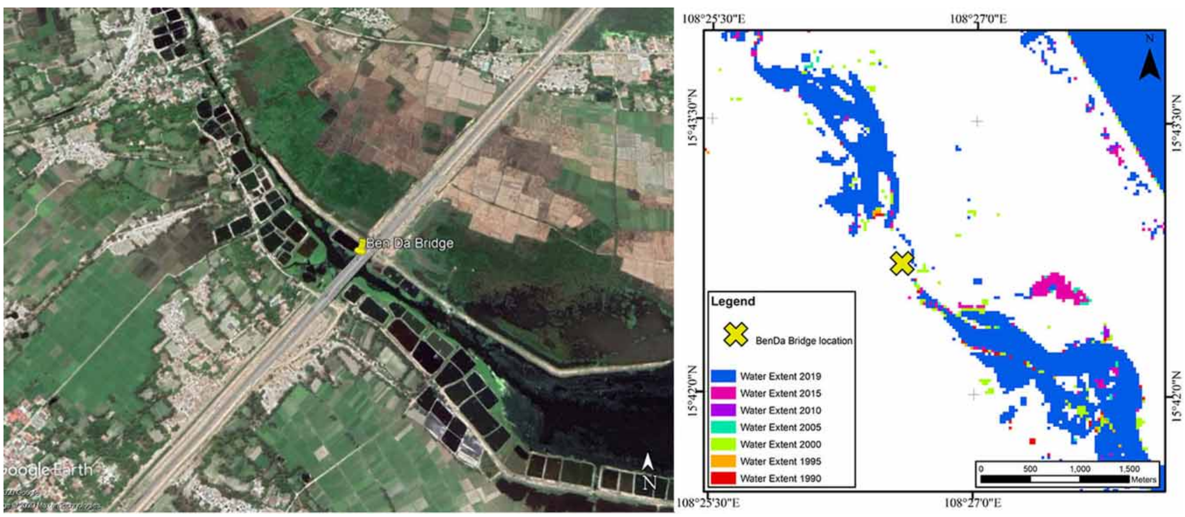


Figure 13 | Location of the Ben Da bridge from Google Earth (left panel) and Sentinel-2 (right panel).

obtained from the General Statistics Office of Vietnam. The extracted area results (blue line) have similar patterns to the annual exploited aquaculture area (red line in Figure 14).

We developed the water transition map from the available data to capture changes between three classes of water coverage i.e., non-water, permanent water, and seasonal water for the Truong Giang river over the past three decades (Figure 15). These

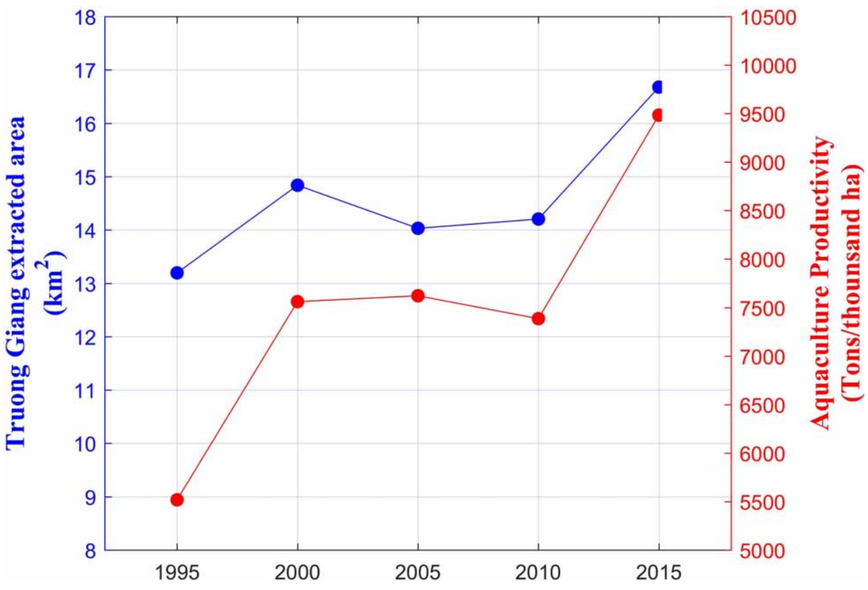


Figure 14 | Extracted area of the Truong Giang river versus aquaculture productivity of Quang Nam province. Please refer to the online version of this paper to see this figure in color: https://doi.org/10.2166/wcc.2021.347.

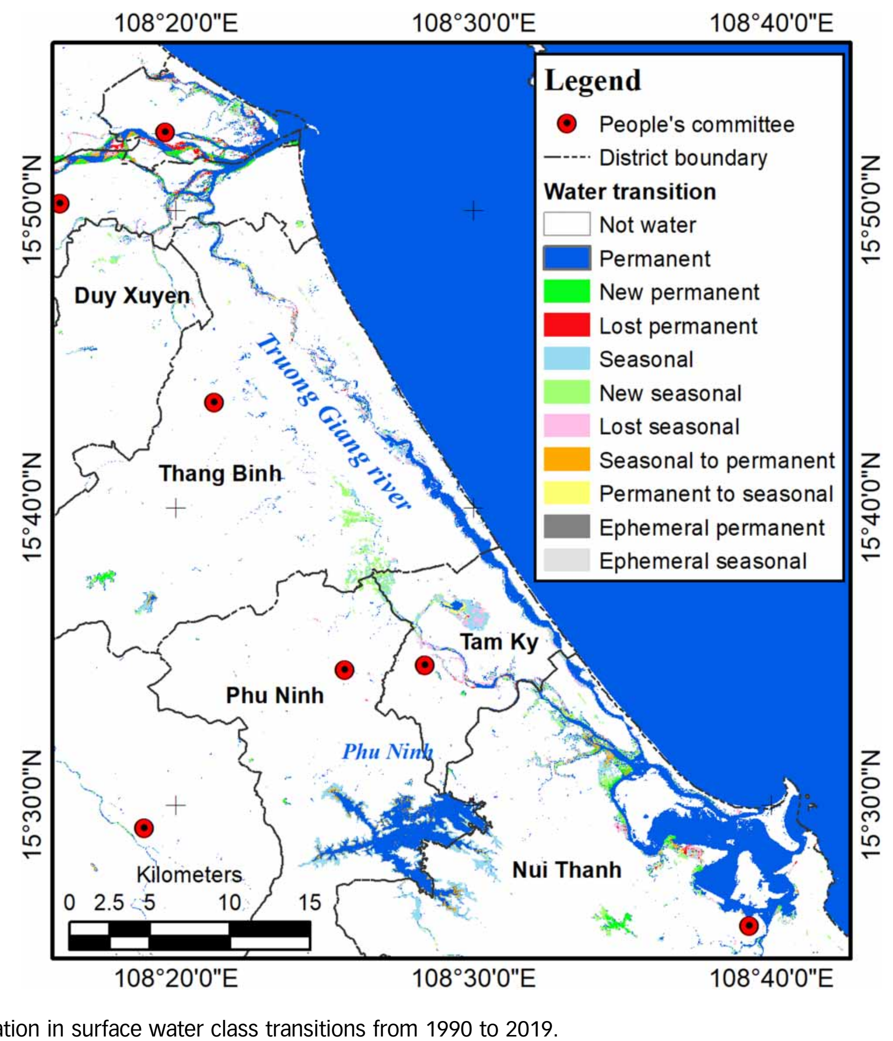


Figure 15 | Wide variation in surface water class transitions from 1990 to 2019.

classes can be delineated as permanent water is the nearly unchanged amount of surface water by time. The map shows a wide variation in surface water in the Truong Giang river and its adjacent area and provides statistics on their extent and change to support better-informed water management decision making. Specifically, long-term effects from the environment and human activities can be clarified, as well as future predictions for changes, i.e., estuarine morphology, sediment, and water resources, can be assessed (De Vriend 2001).

In conclusion, long-term morphological changes in rivers are unpredictable, and it is vital to collect a significant amount of data and implement annual surveys to investigate these changes. Conventional methods, i.e., field surveys and *in situ* measurements, provide highly accurate performance but take significant time and budget to implement. Thus, combining these applications with conventional methods can bring enormous water management benefits (Thakur *et al.* 2017).

5.3. Flood extent detection from satellite images for flood hazard and risk assessment

Floods are catastrophic natural hazards, with detrimental impacts on properties, humans, and the environment over the world (Anusha & Bharathi 2020). Due to climate change, these events are becoming more frequent, requiring local authorities and decision makers to obtain sustainable solutions in reducing and recovering flood damages (Balica *et al.* 2014). Enormous research pieces were implemented to approach flood risk assessment (Brisco *et al.* 2013; Klijn *et al.* 2015; Rahman & Thakur 2018), and a significant number of studies for the Vietnam coastal region were also developed (Balica *et al.* 2014; Chau *et al.* 2015).

From the proposed methodology of this study, the authors extracted flood extent on 5 November 2009, with detrimental influences on population, crops, and facilities (Giang 2010). Firstly, surface water on 8 November 2009, including permanent water and flood extent, was extracted. Permanent water is the amount of water surface that nearly remains unchanged, i.e., lakes, reservoirs, ponds, and flood extent is the expansion of permanent water among the flooded period (Rahman & Thakur 2018). Therefore, a flood extent map was obtained by separating the permanent water from surface water. Figure 16 shows the

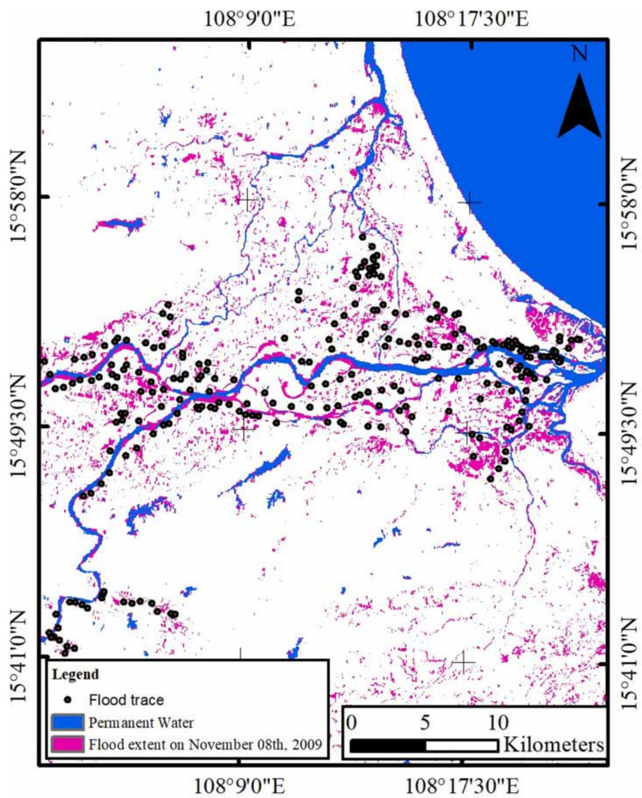


Figure 16 | Flood extent on 8 November 2009. Please refer to the online version of this paper to see this figure in color: https://doi.org/10.2166/wcc.2021.347.

flood extent (pink region) on 8 November 2009, captured by the Landsat satellite with 288 flood traces of the hazardous 2009 flood (dark spots).

Because of the time difference (the flood peak was on November 5 while the image was captured on November 8) and the resolution of medium sensors (10–30 m), only some flood traces were overlapped with the inundated areas because the water was drained. However, the flood extent can still be pointed out, and the region with high-concentrated flood traces was accurate with the extended areas from our extraction (the pink area). To assess the damages for this flood, we combined flood extent extraction with the dataset of cropland and urban area obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) image (Figure 17). About 51,000 people, 7.5 ha of the cropland, and districts along the coastline, including Ngu Hanh Son, Dien Ban, Thang Binh, Tam Ky, and Nui Thanh, suffered severe damage. Mapping affected regions through aspects such as population and cropland, allowing decision makers to provide optimal solutions to reduce and recover from flood damage. The proposed method can save a significant amount of time and money compared with field surveys.

The researchers can still use the extraction performance to determine the affected areas, prepare hazard maps, and rapidly assess the flood impacts from periodically available data. For example, flood hazards can be evaluated by combining flood extent and inundated depth from the Digital Elevation Model (DEM) or the Digital Surface Model (DSM) (Huang *et al.* 2014). Furthermore, if flood vulnerability maps were created in specific regions, damages in several aspects, i.e., Social, Economic, Environmental, and Physical, can be assessed rapidly (Balica *et al.* 2014). Thus, the combination between surface water extraction and available data/maps is more efficient for local authorities in the flood damage assessment process, saving more time than conventional methods such as field surveys.

5.4. Discussion of the proposed method

Thanks to the enhancement and open access of remote sensing technologies, satellite images have become a free, rapid, and worldwide source for researchers and authorities to better understand regional water availability, water storage, and change detection of surface water (Karpatne *et al.* 2016). The continuously long-term acquired and globally covered data can now address the problems of limited information in many areas, especially those that are huge, inaccessible, or dangerous to approach (Herndon *et al.* 2020). Medium spatial resolution sensors, i.e., Landsat series and Sentinel granted by NASA and ESA, provide valuable sources with temporal scales up to 3-day revisit time and spatial resolution up to 10 m (Roy *et al.* 2019). As mentioned in the above sections, the performance of surface water extractions shows good agreement with reference data and performance to apply in water resources management. The proposed method can bring enormous benefits for Vietnamese water resources management and provide solutions to common issues, such as the lack of observed data in a long-term period.

However, some shortcomings need to be addressed. Images with a cloud-covered percentage higher than 50% are hard to process, especially in flooded periods with a high cloud cover percentage. In the following research, the authors consider

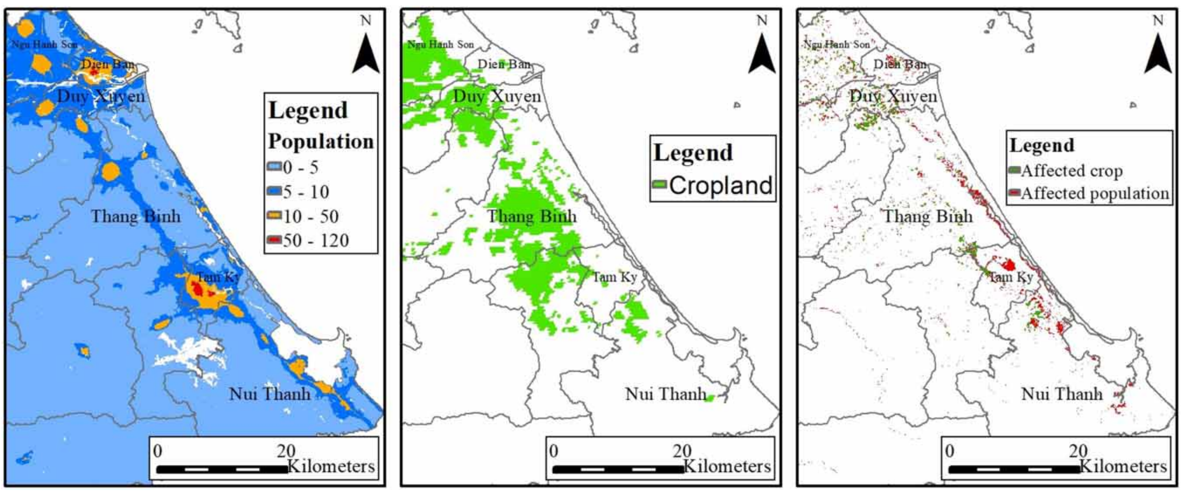


Figure 17 | Rapid flood damage assessment for population and cropland.

using images from the Sentinel-1 SAR satellite (Vuong Tai *et al.* 2021) since SAR sensors can perform even in persistent cloud conditions (Bioresita *et al.* 2018).

6. CONCLUSIONS

In this study, surface water can be detected and extracted from the Landsat and Sentinel satellite images from NDWI and mNDWI indices. The accuracy for surface water extraction of rivers and reservoirs from both indices showed good agreement with *in situ* measurements when the OA and KC values obtained excellent results. The outcomes when applying in three water resources management aspects, which are reservoirs operations, surface water dynamic detection, and flood extent extraction, also show excellent performance and promising abilities in the future.

Quang Nam is considered a potential province for economic development in the Central region of Vietnam. Most economic activities in this province, including hydroelectric, aquaculture, transportation, and tourism, are based on water resources to earn profits. Thus, it is essential to integrate exploitation and maintenance to achieve sustainable management and development in the present and future. By applying remote sensing techniques, particularly processing satellite images, local authorities and researchers can have an alternative method to manage surface water as well as offer satisfactory solutions for the current issues. Moreover, the proposed methodology can address information scarity problems when the field survey data and physically based models are unavailable. This study's applications can be efficiently applied to not only this area but also other regions.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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