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## EDITED BY

Biswajeet Pradhan,  
University of Technology Sydney, Australia

## REVIEWED BY

Bibhuti Bhusan Sahoo,  
Centurion University of Technology and  
Management School of Engineering and  
Technology, India  
Devrajsinh Thakor,  
Indian Council of Agricultural Research-Indian  
Veterinary Research Institute, India

## \*CORRESPONDENCE

Pankaj Kumar,  
✉ pankajdsedu@gmail.com

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# Monitoring the dual-season hydrological dynamics of the Pong reservoir in Himachal Pradesh, India

Rajesh Sarda and Pankaj Kumar\*

Department of Geography, Delhi School of Economics, University of Delhi, New Delhi, India

Reservoir hydrological conditions play a crucial role in both natural and human ecosystems. This study investigates the dual-season (pre-monsoon and post-monsoon) hydrological dynamics of the Pong Reservoir and analyzing the spatial character using Landsat multi-spectral images collected from 1994 to 2024. The 30 years were divided into three phases to assess changes in hydrological consistency and relative water depth over time. The Modified Normalized Difference Water Index (MNDWI) proved effective for mapping the water coverage area of the Pong Reservoir. Analysis based on MNDWI indices reveals significant seasonal fluctuations in water coverage, with 36.18 km<sup>2</sup> of the reservoir exhibiting seasonal characteristics. Furthermore, the phase-wise results indicate a substantial decline in the area of high hydrological consistency during the pre-monsoon season, from 120.54 km<sup>2</sup> in Phase 1 (1994–2004) to 88.49 km<sup>2</sup> in Phase 3 (2015–2024). The change matrix indicates that 10.62 km<sup>2</sup> transformed from higher to lower hydrological consistency classes from Phase 1 to Phase 2, and a further 51.97 km<sup>2</sup> underwent a similar transformation from Phase 2 to Phase 3 in the post-monsoon season. The study employed a spatial linear trend modelling approach to identify trends in relative water depth, revealing a decreasing trend and a quantifiable reduction in the reservoir's depth for both seasons. Additionally, further analysis was conducted on the impact of seasonal rainfall and sedimentation on the hydrological dynamics of the Pong Reservoir. These findings could assist policymakers in formulating effective conservation plans for this important Ramsar site.

## KEYWORDS

reservoir, spatio-temporal analysis, hydrological consistency, relative water depth, linear trend modelling

## 1 Introduction

Anthropogenic function is responsible for maximum modifications of the fluvial landscape features on the regional to global scale, one of which is the construction of dams over rivers (Ekka et al., 2020). The construction of reservoirs to capture surface water is a common practice across the globe (Donchyts et al., 2022). The river damming conception is largely done by prioritising the positive appearance of human wellbeing, viz., socio-economic development, hydro-ecological importance, and environmental advantages. It provides expensive services such as water supply for irrigation, hydroelectric power generation, flood protection, transportation, and recreational activities (Guo et al., 2021; Zhao et al., 2022; Máčová and Kozáková, 2023). On the other side, it significantly affects the downstream rivers hydrological regime, particularly

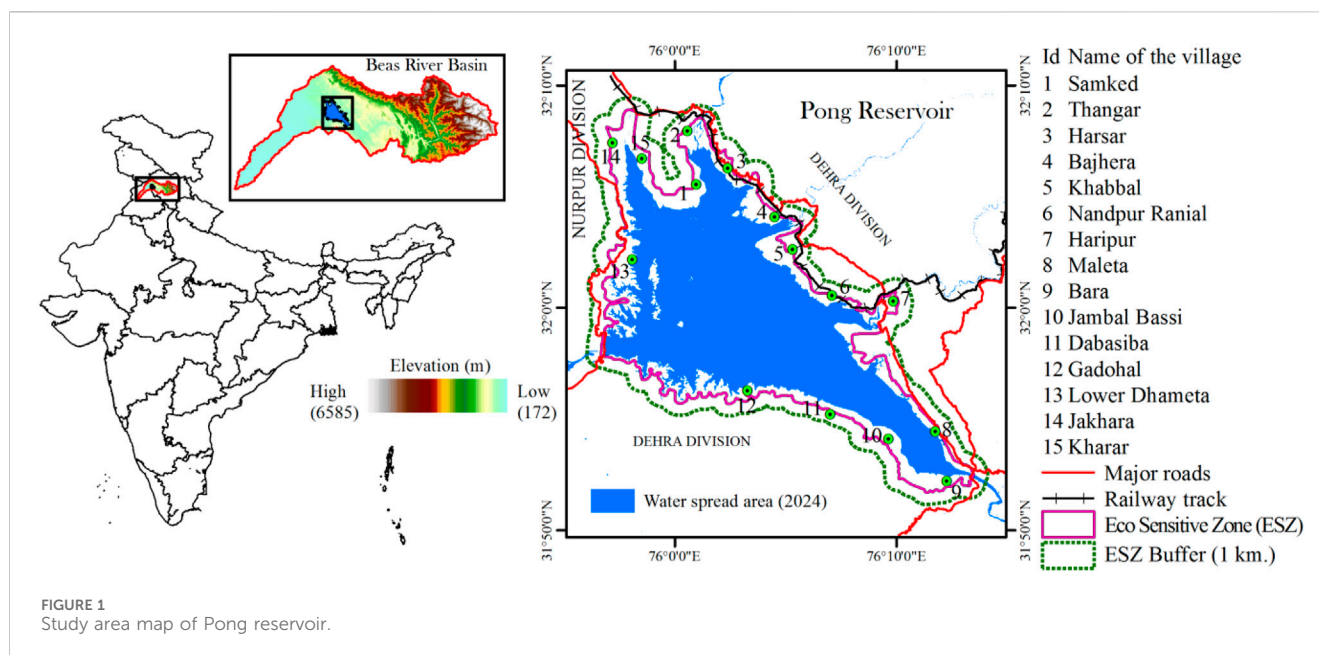
through changes in the magnitude, timing, and recurrence of flows (Haghighi et al., 2014). So, the construction of reservoirs over rivers has both some benefits and burdens (Połomski and Wiatkowski, 2023). Without much extending the benefits burden debate, this discussion focuses solely on the positive aspects of human-made reservoirs, which face some emerging threats (Ho and Goethals, 2019). The excessive water demand due to increasing population, sedimentation, climate change, the inherent variability of precipitation, and river discharge were the major threats to the hydrological character of the reservoir (Ghosh and Chakraborty, 2021; Krztoń et al., 2022; Patro et al., 2022; Verma et al., 2023). All the mentioned threats have reached such an extent that they jeopardize the reliability of reservoir hydrological functions (Ayele et al., 2021).

The hydrological regime of the man-made reservoirs differs significantly from that of natural wetlands, such as rivers and lakes (Sarda and Pal, 2024). The natural wetland strongly depends on rainfall and river inundation for water recharge. However, their outlet systems are often inadequate, resulting in a prolonged period of standing water. In contrast, man-made wetlands typically have more effective outlet systems. While they receive water from natural sources, the discharge from reservoirs is closely regulated by the concerned authorities. Thus, it creates a highly controlled water management system. This regulation leads to distinct hydrological characteristics, including the frequency and magnitude of water level fluctuations, as well as the timing and duration of these changes are quite distinct from those of natural wetlands. These unique characteristics have a substantial impact on the health of the wetland ecosystem. For example, the shallow water depths and limited surface areas make the reservoirs ecologically fragile and less resilient in terms of the aquatic ecosystem. Therefore, a thorough understanding of the hydrological characteristics of a reservoir is not merely a technical exercise but a crucial prerequisite for developing sustainable management strategies and ensuring its long-term viability as a vital environmental resource.

Recent advancements in remote sensing technology have significantly improved the mapping and monitoring of surface water dynamics (Cazenave et al., 2016). This technology offers more accurate and reliable information than conventional *in-situ* measurements due to its ability to monitor the Earth at various spatial and temporal scales continuously (Sogno et al., 2022). The integration of remote sensing data in water resource applications can effectively aid in formulating sustainable management plans. Over time, various approaches have been introduced to delineate water cover areas. Among them, the spectral water indices approach is well-recognised and easy to use for real-time monitoring of surface water across the globe. Various spectral water index techniques have been developed to delineate water bodies from multi-spectral satellite imagery. **Supplementary Table S1** provides a comprehensive overview of different spectral water indices used for mapping surface water cover. These techniques are continually updated and widely used. Based on the literature survey, it can be concluded that the Normalized Difference Water Index (NDWI) is most suitable for delineating open water bodies (McFeeters, 1996). The NDWI, which was designed to extract water features using the green and near-infrared (NIR) bands of the Landsat Thematic Mapper (TM), with a threshold of zero, has been found

ineffective in correctly distinguishing built areas from water surfaces (McFeeters, 1996). In addition to open water bodies, the Modified NDWI (MNDWI) is often suitable for identifying wetlands with wet soil, as well as for clearly depicting reservoir water cover, urban lakes, and river channels. Xu (2006) modified the MNDWI by replacing the NIR band with the middle infrared band of Landsat-5 Thematic Mapper. This modification enhances the contrast between water and non-water features, helping to eliminate signals from built-up areas and dark soils. Recently, the Re-Modified NDWI (RmNDWI) has been successfully applied for wetland mapping (Debanshi and Pal, 2020). Debanshi and Pal (2020) introduced the RmNDWI by using information from the red band instead of the green band. However, not all the water extraction indices are equally applicable across the globe, while the performance of those water extraction indices will vary in different situations (Zhai et al., 2015). Considering this space's respective applicability of the water extraction indices, the present work has attempted to use a multi-index approach and selected the best suitable index via a validation process.

Many researchers have investigated reservoir hydrological dynamics focusing on issues like climate change, sedimentation, and anthropogenic pressure (Amasi et al., 2021; Matlhodi et al., 2021; Kahaduwa and Rajapakse, 2022). Most of the studies primarily focused on the changes in water cover area by using a single-date satellite image, but studies on water cover consistency (dual-season) using multi-date satellite images have not been done yet. Reservoir hydrological consistency in water cover can indicate which part possesses consistent water presence and which areas store water inconsistently or no longer retain it. The water presence frequency approach could be a good measure to examine the reservoir hydrological consistent character (Sarda and Das, 2018; Taheri Dehkordi et al., 2022). It can easily figure out consistent/inconsistent water-retaining reservoir areas at a spatial scale. Therefore, this research will provide valuable references in proposing a sustainable management plan for the reservoir. On the other side, Water depth is another crucial hydrological component, which is directly linked to the species diversity, richness, and comfort (Asher et al., 2017; Yang et al., 2020). However, infrastructures for continuous monitoring of reservoir depth are not always available in all reservoirs. In these circumstances, multi-temporal satellite images can be an effective approach for monitoring the reservoir depth. Most of the studies found the linear relationship between the spectral water index value and depth of surface water (Talukdar and Pal, 2019; Pal and Sarda, 2021; Khatun et al., 2021). So, this study considered the water indices value as the relative depth of the reservoir and examined the spatial hydrological performance over time. Spatial trends in reservoir water depth need to be assessed for any sustainable management planning (Daus et al., 2021). Many researchers investigate historical trends (pixel-wise) for surface water, crop health, and other environmental components using a linear regression modelling approach (Debanshi and Pal, 2020; Pal and Paul, 2021; Pal et al., 2022). Although no studies have been carried out on utilizing a linear trend modelling approach to examine the pixel-wise changes in the hydrological character of the reservoir. Therefore, in this research, we developed a pixel-wise trend map that represents the reservoir hydrological character. The analysis was done by applying a linear regression model, taking into account long-term time series



water indices maps spanning 30 years. As a result, the outcome provides very detailed insights about the changes in the reservoir's hydrological conditions.

This work is very instrumental and could be helpful to the management authorities for formulating any management plans at a very fine scale. So, the essential objectives of this study are summarised as (i) To extract water bodies using different water extraction indices along with validation techniques and select a suitable water index for further analysis; (ii) Monitoring dual season spatio-temporal differences of hydrological consistent areas for 3 decades (1994–2024); and (iii) Recognize the seasonal dynamics of reservoir relative water depth using spatial linear trend modelling approach from 1994 to 2024.

## 2 Study area

Pong Reservoir, located in the Kangra district of Himachal Pradesh, was constructed as an earthen management dam. It is also known as the Maharana Pratap Sagar Reservoir. The Beas River and its tributaries predominantly influence the hydrological dynamics of the reservoir. It is the largest man-made wetland in Northern India, which intercepts the Trans-Himalayan flyway. This man-made wetland was listed as a site of national importance in 1994 and incorporated as a Ramsar site in 2002 based on the immense diversity of waterfowl it supports. Thus, the Union Ministry of Environment and Forests has recently issued a draft notification (on 28 April 2022) declaring an area of 1 km from the boundaries of Pong Dam Wildlife Sanctuary as an Eco-Sensitive Zone (ESZ) (Figure 1). The total coverage area of pong reservoir is 245.29 km<sup>2</sup> including 156.62 km<sup>2</sup> notified as a Ramsar wetland area. The catchment area of the Pong Reservoir covers approximately 12,561 km<sup>2</sup> and has a storage capacity of about 7,290,000,000 m<sup>3</sup>. This reservoir is situated in a subtropical monsoon climate, where maximum rainfall occurs during the monsoon months from June to September. The monsoon rainfall contributes around 57% of the

total annual rainfall, while the post-monsoon period from October to December accounts for about 18% of the total rainfall. The remaining seasons experience low rainfall and high rates of evapotranspiration. As a result, water availability and the surface area of the reservoir are maximum during the monsoon period. For this research, we created a spatial buffer with a radius of 1 km around the Eco-Sensitive Zone (ESZ) of the Pong Reservoir.

## 3 Materials

Landsat satellite images are valuable remote sensing datasets, which are widely used for monitoring landscape features over time. Many researchers used this dataset because of its free availability. In this research work, a total of 170 multi-temporal Landsat satellite images (Level-2) for the pre- and post-monsoon seasons were collected from 1994 to 2024. These satellite images were downloaded from the United States Geological Survey (USGS) Earth Explorer website (Table 1). The details of the sensors and image acquisition dates were mentioned in the supplementary section (Supplementary Table S2). The reservoir area was initially delineated using Google Earth images; however, raw satellite imagery was not useful for extracting information. To enhance its usefulness, the other necessary corrections were made using geospatial software.

## 4 Methods

### 4.1 Method for reservoir water cover area mapping

Many spectral indices have been utilized to identify different landscape features like water body, vegetation, built-up area etc. In this connection, various spectral water indices were developed for mapping water cover area like Normalized Difference Water Index

TABLE 1 Information about the satellite imagery used in this study.

| Key information            | Landsat-5                 | Landsat-7 | Landsat-8 | Landsat-9 |
|----------------------------|---------------------------|-----------|-----------|-----------|
| Sensor                     | TM                        | ETM       | OLI-TIRS  |           |
| Period of acquisition year | 1994–2011                 | 2000–2013 | 2014–2024 | 2022–2024 |
| Total number of images     | 52                        | 58        | 48        | 12        |
| Path/row                   | 148/38                    |           |           |           |
| Spatial resolution (m)     | 30 m                      |           |           |           |
| Note                       | Cloud Cover less than 10% |           |           |           |

(NDWI) (Mcfeeters, 1996), General Water Index (GWI) (Yang and Xu, 1998), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), Water Ratio Index (WRI) (Shen and Li, 2010), New Water Index (NWI) (Feng, 2009), Automated Water Extraction Index (AWEI) (Feyisa et al., 2014), Re-modified Normalized Difference Water Index (RmNDWI) (Debanshi and Pal, 2020) etc. However, the effectiveness of these water indices varies across different regions. In this research work, three spectral water indices (NDWI, MNDWI and RmNDWI) were utilized to delineate reservoir water cover area by using Equations 1–3.

$$NDWI = \frac{Band_{Green} - Band_{NIR}}{Band_{Green} + Band_{NIR}} \quad (1)$$

$$MNDWI = \frac{Band_{Green} - Band_{MIR}}{Band_{Green} + Band_{MIR}} \quad (2)$$

$$RmNDWI = \frac{Band_{Red} - Band_{MIR}}{Band_{Red} + Band_{MIR}} \quad (3)$$

The spectral indices value discussed above vary within the range of −1 to +1. The negative value indicates a land area or non-water region. The value close to 0 suggest a saturated water body with a shallow depth, while a value close to 1 indicate a water body with greater depth (Gao, 1996).

## 4.2 Validating inundation area maps

The water cover areas of the Pong Dam have been extracted for different years with above above-stated indices and further compared with the extracted values by applying the polygon method on historical images received from Google Earth. This approach refers to the quantitative difference between the actual area (using the polygon method from Google Earth) and the estimated area (using water extraction indices from a satellite image) by using Equation 4. Here, the actual area is the base of validation. Due to no alternative source of ground truth data other than Google Earth images for past years, this method is sufficient for real-time visual interpretation. Here, the calculated output would be positive or negative.

$$V_{image-based} = \begin{cases} RA_{actual} - RA_{estimated} = d_0 \\ RA_{actual} - RA_{estimated} = d_1 \end{cases} \quad (4)$$

Where,  $V_{image-based}$  = Image-based validation;  $RA_{actual}$  = Actual reservoir area (km<sup>2</sup>) derived from water extraction indices;  $RA_{estimated}$  = Estimated reservoir area (km<sup>2</sup>) from Google Earth

image;  $d_0$  = the value is close to zero suggest more accurate;  $d_1$  = the value is far from zero suggest less accurate (positive or negative).

For the point-based accuracy assessment, 132–150 reservoir sites were selected from Google Earth images spanning 3 years (2004, 2014, and 2020). In the most recent year (2024), 68 reservoir sites were randomly taken from the field survey. Using this data, overall accuracy and the Kappa coefficient (K) (Monserud and Leemans, 1992) were calculated for all the utilized indices (Equation 5).

$$Kappa (K) = \frac{P \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{i+} \times x_{+i})}{P^2 - \sum_{i=1}^r (x_{i+} \times x_{+i})} \quad (5)$$

where P refers to the total number of pixels; r refers to the number of rows in the matrix;  $x_{ii}$  is equal to the number of observations in row i and column ii, and  $x_{i+}$  and  $x_{+i}$  refer to the marginal totals for row i and column i.

## 4.3 Computing the hydrological consistency of the reservoir and its seasonal/temporal dynamics

Hydrological consistency signifies the frequency of water presence in each pixel (Borro et al., 2014) within a reservoir domain, and it is very useful for monitoring hydrological dynamics. This information is vital for identifying stable and unstable parts of water bodies on a seasonal and temporal scale. The area characterised by irregular water presence can be considered as hydrologically vulnerable (Sarda and Das, 2018). For hydrologically consistent area mapping, the time series MNDWI water index maps were used for both pre- and post-monsoon seasons. The reservoir water domain mappings were converted into binary maps, providing 1 to the water and 0 to non-water pixels. Binary maps of all the selected years were summed and divided by the number of years considered for the calculation (Equation 6). It could be expressed in percentages (0%–100%). The hydrological consistency value close to 100% indicates that the presence of water in a pixel is almost consistent. This approach has been successfully employed by several researchers for mapping hydrological consistency of wetlands (Borro et al., 2014; Das and Pal, 2017; Saha et al., 2024). Further, it was classified into five classes, such as Very High (>80%), High (60%–80%), Moderate (40%–60%), Low (20%–40%), and Very Low (<20%). The class belongs to Very High and Very Low in both seasons can confirm the high and low hydrological consistency respectively. Additionally, to examine the



transformation of the hydrological consistent area, the 30 years were divided into three phases, e.g., Phase-1 (1994–2004), Phase-2 (2005–2014), and 2015–2024 as Phase-3. A change detection technique was applied between Phase 1 (1994–2004) and Phase 2 (2005–2014), and between Phase 2 (2005–2014) and Phase 3 (2015–2024) to investigate the temporal shift of areas among the classes of hydrological consistency.

$$HC_j = \frac{\sum_{i=1}^n W_j}{n} \times 100 \quad (6)$$

$HC_j$  = Hydrological Consistency of  $j^{\text{th}}$  pixels in a period;  $W_j$  =  $j^{\text{th}}$  pixel having water in the selected MNDWI images;  $n$  = number of images.

#### 4.4 Computing the relative water depth of the reservoir and its dynamics

The hydrological consistency (HC) method is an alternative approach for mapping consistent water cover area by utilizing the frequency of water presence (Taheri Dehkordi et al., 2022). This technique only shows the spatial extent of a water body, but does not capture the variations in the water depth (intensity of MNDWI score) for each pixel during the study years. Generally, the value (for a water body) varies from 0 to 1. Where '1' represents high-level water presence and a higher depth of water within the water bodies. The Water Indices score cannot offer a definite water depth, but qualitatively, it represents the equivalent (Gao, 1996). Several studies have found a linear relationship between the intensity of water indices scores and water depth in similar environments (Talukdar and Pal, 2019; Debanshi and Pal, 2020; Pal and Sarda, 2022). However, High eutrophication and turbidity may interrupt the straightforward relation many times (Talukdar and Pal, 2019). In this study, the spectral water index score is considered as a proportional representation of the reservoir's relative water depth. Equation 7 was used to quantify the phase-wise relative water depth over the Pong reservoir.

$$RWD = \frac{\sum_{i=1}^n I_x}{N} \quad (7)$$

Where  $RWD$  denotes the relative water depth of the reservoir;  $I_x$  the images used in an  $x$ -th period;  $N$  is the total number of years taken into consideration.

For a better understanding of the relative water depth dynamics, the Coefficient of Variation (CV) approach has been used. This approach simply calculates the fluctuation in the Modified Normalized Difference Water Index (MNDWI) score for each pixel, as described in Equation 8. This section focuses on the internal dynamics of relative water depth within the reservoir. It is logically suggested that the pixels exhibit minimal variations in the MNDWI score, represent the hydrologically stable area of the reservoir. Conversely, unstable areas show significant fluctuations in the MNDWI score. Such unstable regions in the reservoir are vulnerable to hydrological and ecological sustainability. For instance, a pixel that retains a deeper water depth 1 year may completely dry out the next year, leading to a higher CV value. In contrast, pixels with consistently show either high or low MNDWI

values are expected to have a low CV score. This analysis indicates stable or unstable reservoir areas, which are critical for the sustainability of species adapted to those specific hydrological conditions.

$$CV = \frac{\sigma}{\mu} \times 100 \quad (8)$$

Where,  $\sigma$  is the standard deviation,  $\mu$  refers mean score of a given period of the dataset

The above-mentioned approach captures the degree of fluctuation, which signifies the level of consistency, but cannot portray the trend of relative water depth over the region. Therefore, linear regression trend modelling can be adopted to bring out the trend. Here, the pixel-wise linear regression model (Equation 9) has been run in the water body pixels to show the degree of change. It is a very simple and effective way to measure, which focuses on the time series spatial data. This method was successfully applied for detecting the trends of surface water depth in the wetlands (Debanshi and Pal, 2020; Paul and Pal, 2020).

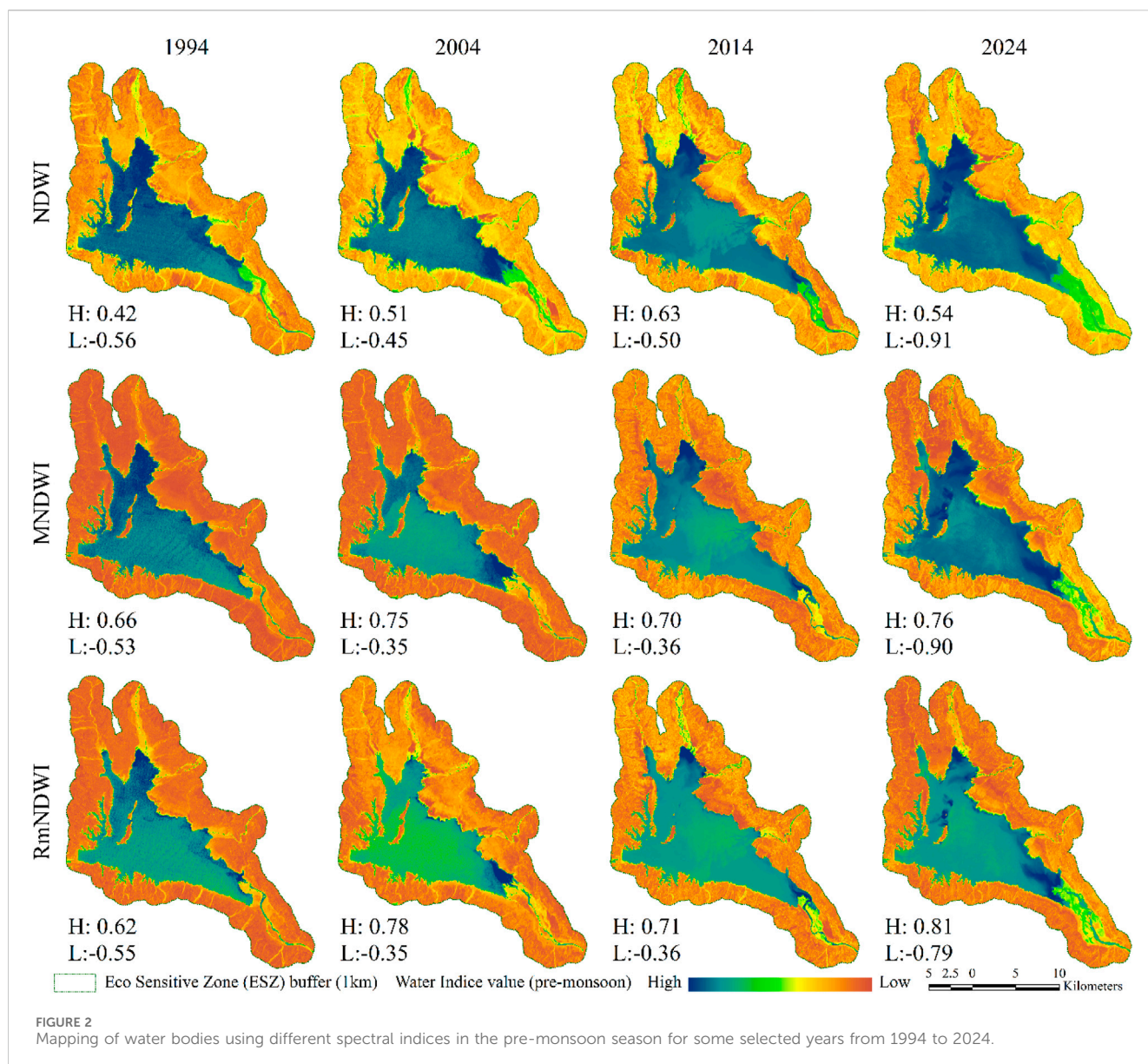
$$Yc = \alpha + \beta X \quad (9)$$

Regression slope ( $b$ ) and coefficient of determination ( $R^2$ ) have also been computed for each pixel, which shows the direction and degree of change in the MNDWI score. A high  $R^2$  value indicates a strong change in the MNDWI score over the period, which also indicates the change in the thickness of water in the reservoir. But no studies have been conducted so far on the application of reservoir water state monitoring. Therefore, to the best of the authors' knowledge, the present study was the first study that utilized a spatial trend model for assessing the reservoir hydrological condition at the pixel scale. This analysis provides a quantitative assessment of the overall hydrological condition of a reservoir system.

## 5 Result and analysis

### 5.1 Spatio-seasonal inundation area dynamics and its validation

Figures 2, 3 show the delineation of water bodies based on different types of water body extraction indices like NDWI, MNDWI, and RmNDWI in the range of 10 years (1994, 2004, 2014, and 2024) for pre- and post-monsoon seasons. Essentially, this method is effective on satellite imagery. Consequently, these kinds of water extraction indices were separated by water body and non-water body in a certain numerical range, and those values can be either positive or negative. The areal pattern of the water spread area was mapped by those three water extraction indices. The post-monsoon season recorded maximum spatial water coverage compared to the pre-monsoon season. In each year, NDWI indices reflect the low areal extent compared to the other two indices (MNDWI and RmNDWI), where MNDWI spectral indices show maximum wetland areal coverage. For example, in 1994, the water cover areas during pre- and post-monsoon seasons were 134.60 km<sup>2</sup> and 229.96 km<sup>2</sup> respectively. While in 2004, the areal extent were 137.62 and 186 km<sup>2</sup>, and in 2024, it stands



123.80 km<sup>2</sup> and 223.26 km<sup>2</sup> (Table 2). Since rainfall and river inflow are the main sources of reservoir water, based on seasonal variability of rainfall, a significant difference in water cover area within the reservoir was recorded between pre- and post-monsoon seasons.

Two types of validation approaches (image-based and point-based) were conducted for accuracy assessment of three water indices maps (NDWI, MNDWI, RmNDWI). In the image-based approach, the actual water cover area was digitized using Google Earth Pro images for the accuracy of the water spread area. The actual area was then compared to the areas determined by the water extraction indices. The reservoir water cover areas extracted through the polygon method from Google Earth images were 175.88 km<sup>2</sup>, 202.74 km<sup>2</sup>, 220.88 km<sup>2</sup> and 228.66 km<sup>2</sup> for the years 2004, 2014, 2020 and 2024 respectively. Table 3 depicts the result of the polygon-based accuracy assessment. The result indicates that the Normalized Difference Water Index (NDWI) performed well, showing a surface water area of 179.78 km<sup>2</sup> for the year 2004. Further seen in the years

2014, 2020, and 2024 the MNDWI index output (193.69 km<sup>2</sup>, 217.85 km<sup>2</sup>, and 233.78 km<sup>2</sup>) aligns relatively well with the areas identified in Google Earth images.

Table 4 presents the results of the point-based accuracy assessment for various water indices (NDWI, MNDWI, and RmNDWI). In the point-based evaluation, it is clear that all indices accurately depicted the water cover area from 2004 to 2024 across both seasons. The level of correspondence between the map and actual conditions ranges from good to excellent for all the indices. Comparing the extracted results using different indices, it was determined that the MNDWI method is the most suitable for mapping water coverage in the reservoir. While MNDWI is structurally similar to NDWI, it utilizes the shortwave infrared (SWIR) band instead of the near-infrared (NIR) band. This adaptation makes MNDWI an improvement over NDWI, as water features absorb more energy in the SWIR band (Xu, 2006). Further studies were conducted using the MNDWI water index.



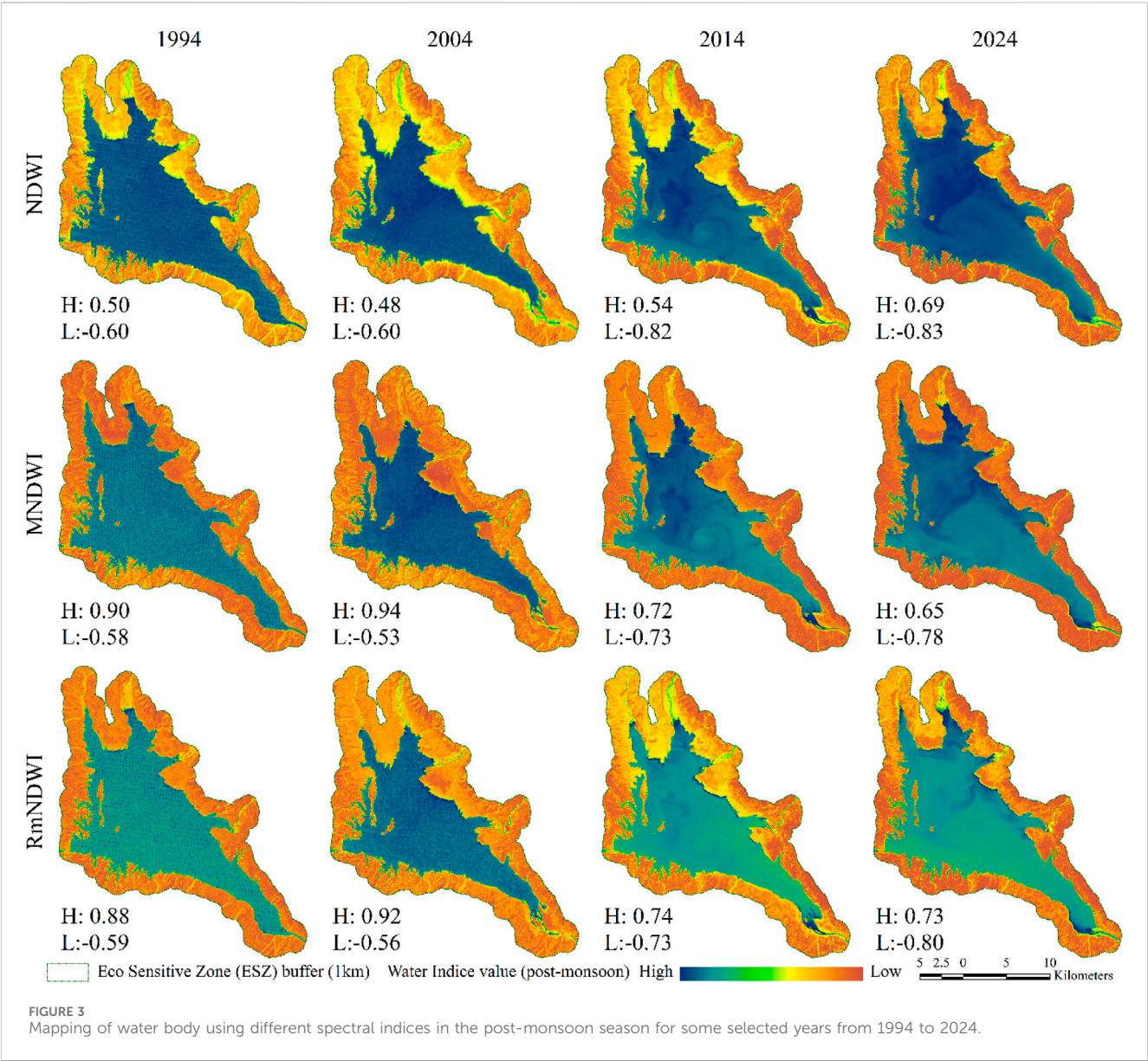


TABLE 2 Areal statistics of the Pong reservoir for pre- and post-monsoon seasons.

| Year | Area (Km <sup>2</sup> ) for the pre-monsoon season |        |        | Area (Km <sup>2</sup> ) for the post-monsoon season |        |        |
|------|----------------------------------------------------|--------|--------|-----------------------------------------------------|--------|--------|
|      | NDWI                                               | MNDWI  | RmNDWI | NDWI                                                | MNDWI  | RmNDWI |
| 1994 | 138.67                                             | 134.60 | 135.20 | 231.33                                              | 229.96 | 228.75 |
| 2004 | 144.03                                             | 137.62 | 149.19 | 179.78                                              | 186.00 | 182.49 |
| 2014 | 151.75                                             | 153.90 | 153.03 | 191.28                                              | 193.69 | 192.35 |
| 2024 | 112.97                                             | 123.80 | 122.74 | 220.35                                              | 223.26 | 222.79 |

5.2 Trend of the inundation area and seasonal water depth

Seasonal and temporal variations in inundation area and intensity of MNDWI were observed through time series analysis. The findings indicated that the inundation area, maximum and average MNDWI

intensity exhibited a declining trend from 1994 to 2024 during both pre- and post-monsoon periods (Figure 4). The trends for maximum MNDWI value (excluding pre-monsoon) and average MNDWI value were determined to be negative, with a probability value of less than 0.05 for both pre- and post-monsoon seasons. A reduction in the maximum MNDWI value either indicates increased

TABLE 3 Accuracy assessment result of the polygon-based approach using Google Earth images.

| Year | Actual area (km <sup>2</sup> ) | Estimated area (km <sup>2</sup> ) |            |        |            |        |            |
|------|--------------------------------|-----------------------------------|------------|--------|------------|--------|------------|
|      |                                | NDWI                              |            | MNDWI  |            | RmNDWI |            |
|      |                                | Area                              | Difference | Area   | Difference | Area   | Difference |
| 2004 | 175.88                         | 179.78                            | −3.9       | 186    | −10.12     | 182.49 | −6.61      |
| 2014 | 202.74                         | 191.28                            | 11.46      | 193.69 | 9.05       | 192.35 | 10.39      |
| 2020 | 220.88                         | 211.82                            | 9.06       | 217.65 | 3.23       | 213.88 | 7          |
| 2024 | 228.66                         | 220.35                            | 8.31       | 223.26 | 5.4        | 222.69 | 5.97       |

TABLE 4 Overall accuracy and kappa statistics of water coverage area for pre- and post-monsoon seasons.

| Year | Indices | Pre-monsoon      |                    | Post-monsoon     |                    |
|------|---------|------------------|--------------------|------------------|--------------------|
|      |         | Overall accuracy | Kappa Co-efficient | Overall accuracy | Kappa Co-efficient |
| 2004 | NDWI    | 93.77            | 0.87               | 91.67            | 0.87               |
|      | MNDWI   | 95               | 0.89               | 96               | 0.92               |
|      | RmNDWI  | 95               | 0.89               | 94               | 0.89               |
| 2014 | NDWI    | 91.33            | 0.82               | 94               | 0.88               |
|      | MNDWI   | 95               | 0.92               | 95.33            | 0.9                |
|      | RmNDWI  | 94               | 0.91               | 94               | 0.9                |
| 2020 | NDWI    | 91               | 0.85               | 92               | 0.85               |
|      | MNDWI   | 96.61            | 0.9                | 95               | 0.91               |
|      | RmNDWI  | 93               | 0.87               | 93               | 0.87               |
| 2024 | NDWI    | 93               | 0.84               | 91               | 0.88               |
|      | MNDWI   | 96.56            | 0.93               | 97               | 0.94               |
|      | RmNDWI  | 94               | 0.9                | 95.5             | 0.92               |

sedimentation or a contraction in the water-covered area. This also demonstrated a reduction in relative water depth over time. Although the water-covered area displayed temporary fluctuations, but its overall trend has been negative in both the pre-monsoon and post-monsoon seasons over the past 30 years, suggesting a reduction in water availability within the reservoir.

There were noticeable fluctuations in the reservoir area for both pre- and post-monsoon seasons. This section also presents phase-wise changes in the seasonal area of the reservoir. From the result, it was evident that the areal fluctuations ranged from 7% to 27% for pre-monsoon and post-monsoon seasons respectively (Table 5). During the pre-monsoon season, the average area was 158.59 km<sup>2</sup> in Phase-1 (1994–2004), which reduced to 137.66 km<sup>2</sup> in Phase-3 (2015–2024). A similar declining trend was observed in the post-monsoon season, where the average area was approximately 219.04 km<sup>2</sup> in Phase-1, but it stands at 212.13 km<sup>2</sup> in the recent phase (2015–2024). Table 4 also depicts that in the post-monsoon season, the coefficient of variation (CV) value was lower than the pre-monsoon season due to the higher concentration of rainfall during the monsoon season, which primarily contributed to filling the reservoir area.

### 5.3 Anomaly of reservoir area and the intensity of MNDWI score

Anomaly detection is a widely used technique employed by many researchers to address the extreme occurrences in long-term time series datasets (Saini et al., 2020; Soriano-Vargas et al., 2021). To identify an anomaly, a minimum of 30 years of data is typically required, as shorter datasets may not capture the signals of variability (Stevens-Rumann et al., 2018). Figure 5 provides a visual representation of long-term anomalies in maximum MNDWI score, average MNDWI score, and inundation area for both pre- and post-monsoon seasons from 1994 to 2024. Positive anomaly values are higher than the long-term average value, while negative anomaly value denotes the opposite and *vice versa*. The deeper part of the reservoir is identified by the maximum MNDWI score. The anomaly value for the maximum MNDWI score ranges from −2.33 to 2.61 and −1.57 to 2.48 in pre- and post-monsoon seasons. A good many years registered a positive anomaly of average MNDWI; however, after 2012, all the years recorded a significant reduction of average MNDWI score with a negative anomaly. The drastic reduction (anomalies) was observed in both pre- and post-



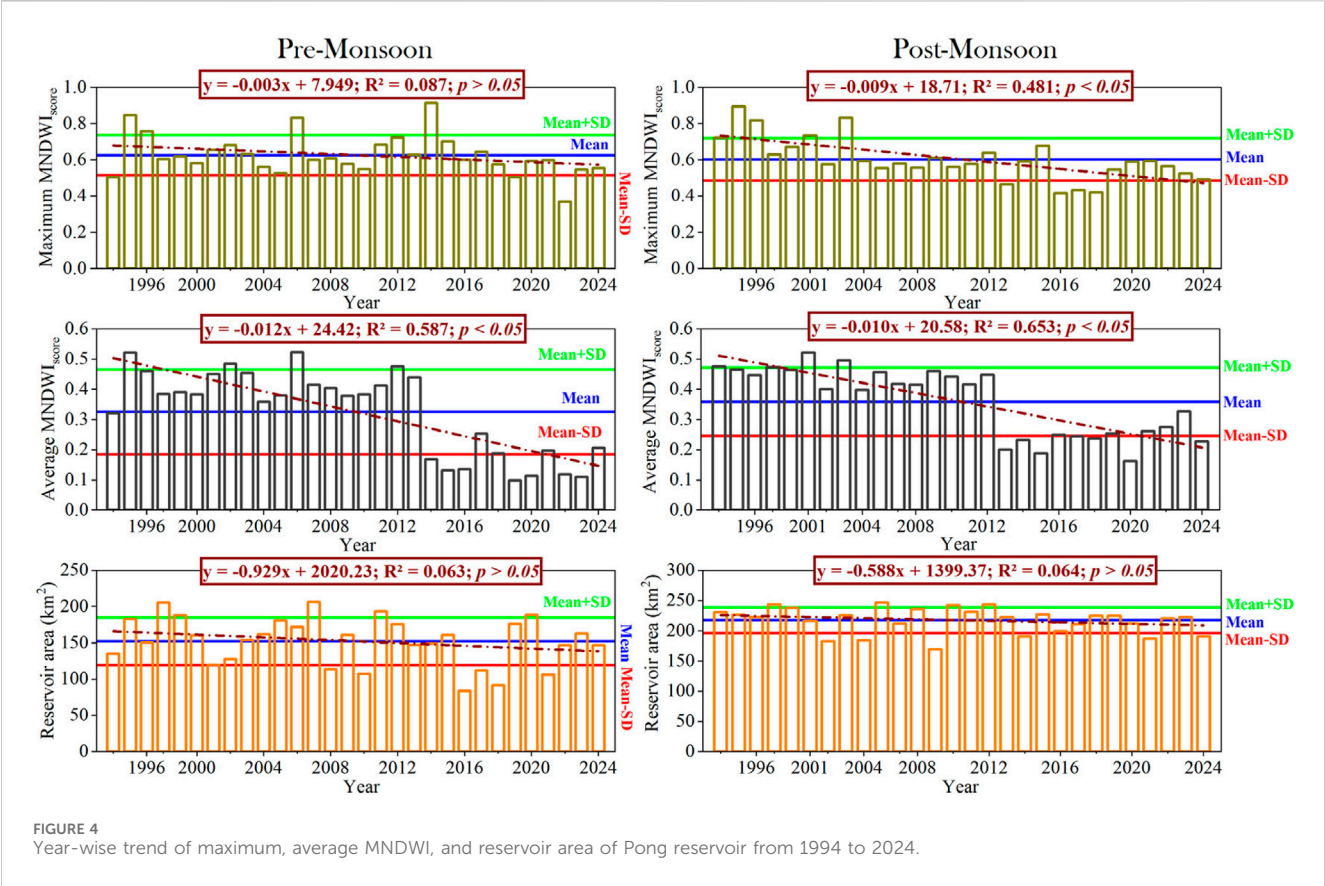


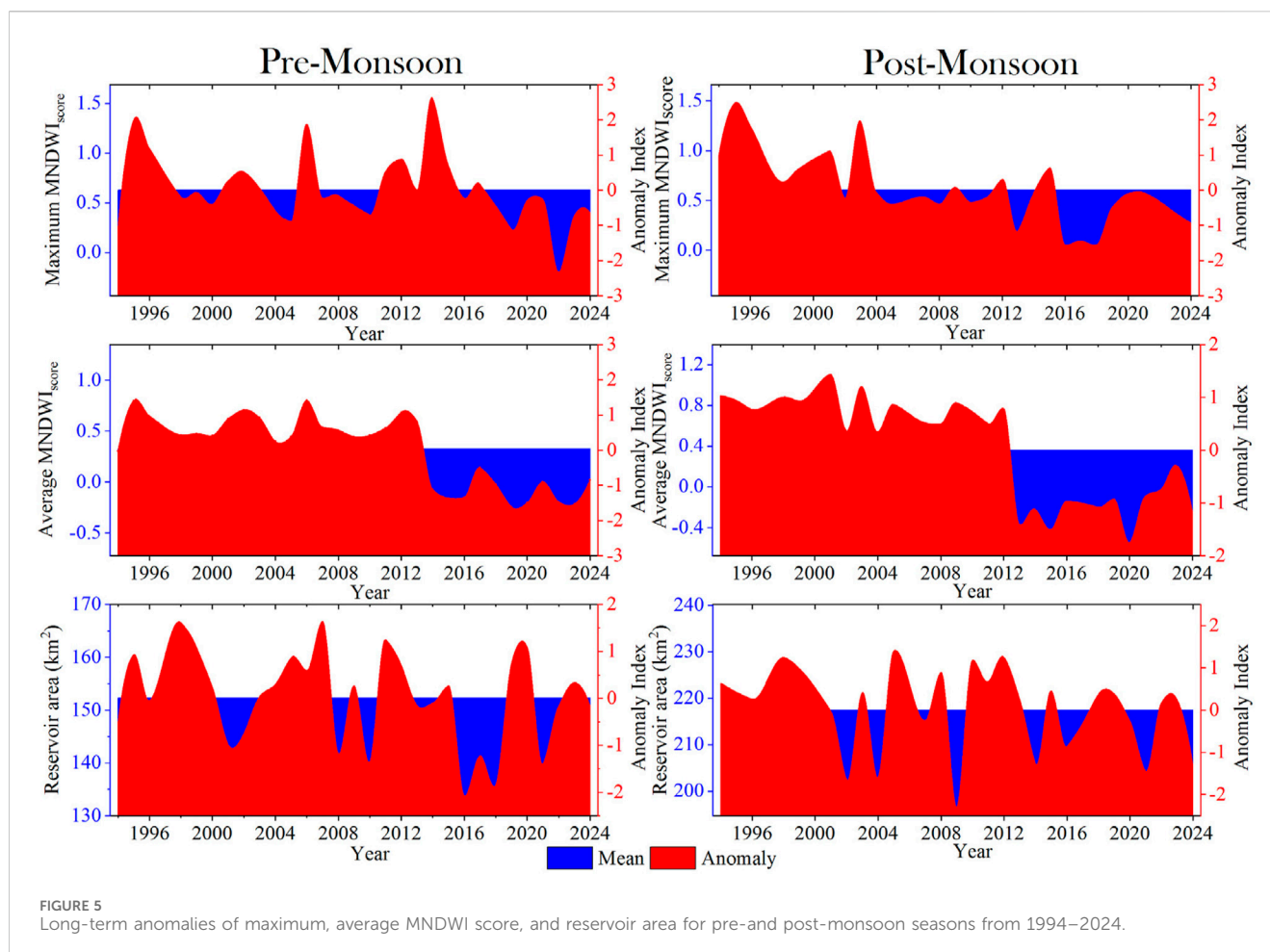
TABLE 5 Phase-wise seasonal areal fluctuation analysis of Pong reservoir.

| Season       | Period    | Average area (km <sup>2</sup> ) | CV (%) | Yc = a+bx               | R <sup>2</sup> |
|--------------|-----------|---------------------------------|--------|-------------------------|----------------|
| Pre-monsoon  | 1994–2024 | 152.29                          | 21.65  | $y = -0.9296x + 2020.2$ | 0.06           |
|              | 1994–2004 | 158.59                          | 17.31  | $y = -1.633x + 3423.4$  | 0.04           |
|              | 2005–2014 | 160.64                          | 20.07  | $y = -2.5819x + 5348.9$ | 0.06           |
|              | 2015–2024 | 137.66                          | 26.71  | $y = -4.0075x - 7955.6$ | 0.11           |
| Post-monsoon | 1994–2024 | 217.44                          | 9.64   | $y = -0.5881x + 1399.4$ | 0.06           |
|              | 1994–2004 | 219.04                          | 9.87   | $y = -3.6492x + 7514.1$ | 0.37           |
|              | 2005–2014 | 221.73                          | 11.97  | $y = -2.0238x + 4289.4$ | 0.05           |
|              | 2015–2024 | 212.13                          | 7.06   | $y = -1.4637x + 3168$   | 0.09           |

monsoon seasons. This indicates a sharp decline in the relative water depth of this reservoir, which is a major concern for the long-term operation of the reservoir. The anomaly value ranges from −1.41 to 1.62 for pre-monsoon and −1.75 to 1.44 for post-monsoon seasons. Seasonal variation of the reservoir water coverage area was also very evident from Figure 5. However, the yearly fluctuation of the inundation area and the frequency of negative anomalies were maximum in recent years for both seasons. The anomaly value (reservoir area) ranges from −2.08 to 1.65 for the pre-monsoon and −2.30 to 1.40 for the post-monsoon season. This suggests that the water coverage area of the reservoir declined over the period (1994–2024).

## 5.4 Spatio-seasonal hydrological consistency of the reservoir

The water body for each year has been composited to show the pixels where it appears either consistent or inconsistent. It is assumed that if a pixel shows a water body frequently, it qualifies as a hydrologically consistent area. Based on this approach, Hydrological consistency has been calculated for both the pre-monsoon and post-monsoon seasons, as displayed in Figure 6. To enhance clarity, each map has been categorized into five classes: very high, high, moderate, low and very low. The very high zone is considered hydrologically and ecologically sustainable,



whereas the very low zone is prone to issues with water retention. Variability in rainfall and river flow might contribute to the increase in the wetted area of the reservoir through inflow and outflow operations. **Figure 6** shows the phase-wise hydrological consistency of the Pong reservoir in pre- and post-monsoon seasons from 1994 to 2024. From the years 1994–2024, out of the total area, 5% and 9% of areas were recorded as having very low hydrological consistency (below 20%), which is susceptible to conversion in both pre- and post-monsoon seasons. Only about 25% and 42% of areas were recorded as very high (above 80%) hydrologically consistent areas. The outcomes indicate that the reservoir can be considered reliable for water-based planning in both seasons. The analysis of hydrological consistency clearly shows that the outer part or fringe area of the reservoir was gradually losing its consistent characteristics, particularly during the pre-monsoon season. The situation of hydrological consistency in the post-monsoon season was quite different from the pre-monsoon season. The result shows that hydrological consistency within the reservoir would be high in the post-monsoon season. **Table 6** depicts the phase-wise areal extent of reservoir areas under different hydrological consistency classes for pre- and post-monsoon seasons. In the recent phase (2015–2024), the total area classified as having very high consistency was 88.49 km<sup>2</sup>, indicating a reduction of about 36% from Phase-1 (1994–2004) during the pre-monsoon season. Conversely, the area classified as having very high consistency in the post-monsoon

season showed a slight increase (about 1%). However, there was a significant reduction of about 40% in the area classified as high consistency over the past 30 years during the post-monsoon season. The proportion of area under the very low hydrological consistent zone was found to be drastically reduced (about 64%), against the general trend, which was practically due to the complete wiping out of a wider part of the fringe reservoir area in the post-monsoon season. It does indicate growing hydrological uncertainty in the reservoir. An increase in uncertainty implies a growing vulnerability in water storage. The rising inconsistency across a larger reservoir area raises concerns regarding the future reliability of water supply from the reservoir.

## 5.5 Phase-wise changes in the hydrological consistency character of Pong reservoir

To better understand the changes in hydrological classes between Phase-1 (1994–2024) and Phase-2 (2005–2014), as well as between Phase-2 and Phase-3 (2015–2024), a change detection analysis was conducted. The results are illustrated in **Figure 7**, while **Table 7** presents the areal transformations from one consistency class to another for each phase. In the pre-monsoon season, approximately 158.24 km<sup>2</sup>, representing 72%, and 121.22 km<sup>2</sup>, or 55%, of the wetland area remained unchanged in terms of

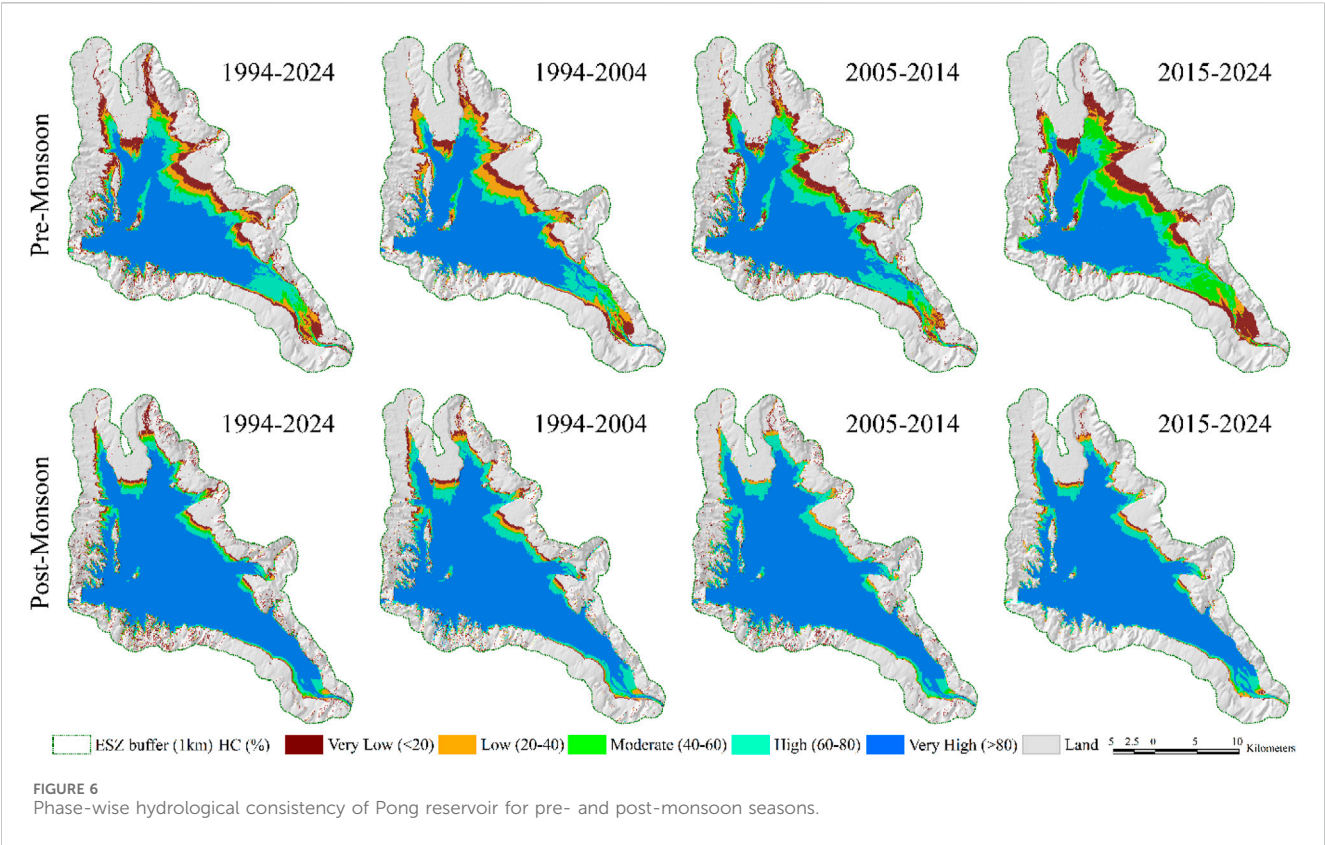


TABLE 6 Season-wise areal extent of different hydrological consistency classes.

| Season       | Hydrological consistency class (%) | 1994–2024               |       | 1994–2004               |       | 2005–2014               |       | 2015–2024               |       |
|--------------|------------------------------------|-------------------------|-------|-------------------------|-------|-------------------------|-------|-------------------------|-------|
|              |                                    | Area (km <sup>2</sup> ) | in %  | Area (km <sup>2</sup> ) | in %  | Area (km <sup>2</sup> ) | in %  | Area (km <sup>2</sup> ) | in %  |
| Pre-Monsoon  | Land                               | 242.32                  | 52.12 | 254.04                  | 54.65 | 251.64                  | 54.13 | 263.32                  | 56.64 |
|              | Very Low (<20)                     | 39.64                   | 8.53  | 25.36                   | 5.45  | 32.52                   | 6.99  | 37.26                   | 8.01  |
|              | Low (20–40)                        | 21.12                   | 4.54  | 27.73                   | 5.96  | 12.73                   | 2.74  | 13.36                   | 2.87  |
|              | Moderate (40–60)                   | 13.94                   | 3.00  | 11.48                   | 2.47  | 15.63                   | 3.36  | 35.35                   | 7.60  |
|              | High (60–80)                       | 33.32                   | 7.17  | 25.73                   | 5.53  | 39.79                   | 8.56  | 27.11                   | 5.83  |
|              | Very high (>80)                    | 114.53                  | 24.64 | 120.54                  | 25.93 | 112.58                  | 24.22 | 88.49                   | 19.04 |
| Post-Monsoon | Land                               | 206.14                  | 44.34 | 211.25                  | 45.44 | 210.01                  | 45.18 | 234.03                  | 50.34 |
|              | Very low (<20)                     | 23.00                   | 4.95  | 17.45                   | 3.75  | 12.83                   | 2.76  | 6.33                    | 1.36  |
|              | Low (20–40)                        | 9.45                    | 2.03  | 13.16                   | 2.83  | 10.12                   | 2.18  | 10.68                   | 2.30  |
|              | Moderate (40–60)                   | 12.23                   | 2.63  | 4.79                    | 1.03  | 6.86                    | 1.48  | 4.64                    | 1.00  |
|              | High (60–80)                       | 20.93                   | 4.50  | 34.87                   | 7.50  | 33.94                   | 7.30  | 24.91                   | 5.36  |
|              | Very high (>80)                    | 193.14                  | 41.55 | 183.37                  | 39.44 | 191.12                  | 41.11 | 184.29                  | 39.64 |

Hydrological Consistency (HC) character. About 12.44 km<sup>2</sup> (Phase-1 to Phase-2) and 55.87 km<sup>2</sup> (Phase-2 to Phase-3) of very high and high hydrologically consistent wetland areas were transformed into relatively lower categories in the pre-monsoon season. About 32.68 km<sup>2</sup> of area in the pre-monsoon season was recorded, where hydrological consistency was improved from Phase 1 to Phase 2. But in the next cycle (Phase-2 to Phase-3), it was reduced significantly, and about 8.77 km<sup>2</sup> of the area maintained the improvement in their hydrological consistency. Qualitative degradation of the hydrological consistency was more prominent



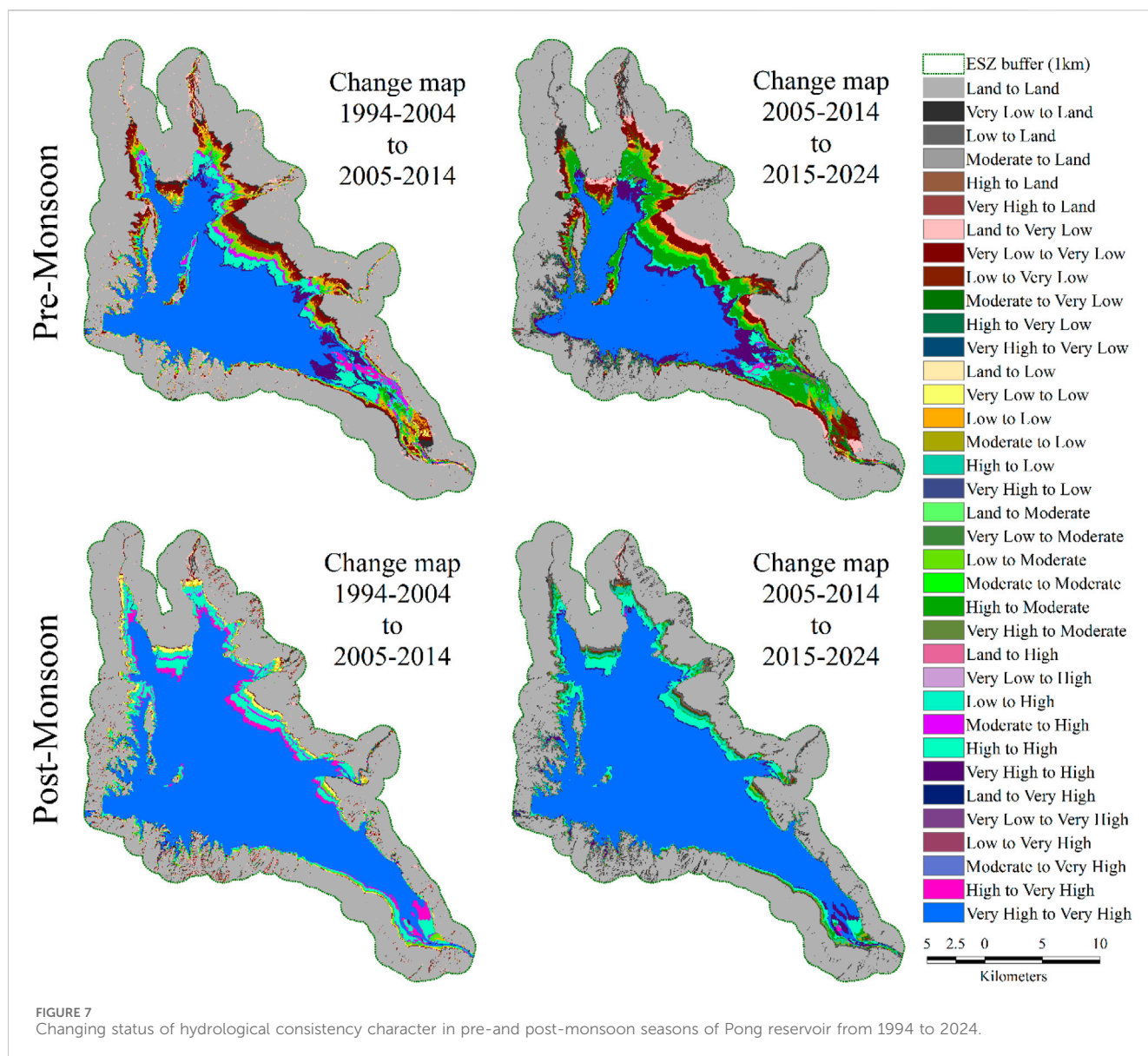


FIGURE 7  
Changing status of hydrological consistency character in pre- and post-monsoon seasons of Pong reservoir from 1994 to 2024.

in the outer areas of the reservoir. This fact was also true for the post-monsoon season. For the post-monsoon season, 3.72 km<sup>2</sup> and 24.24 km<sup>2</sup> areas were drastically wiped out (converted to land) from Phase-1 to Phase-2 and from Phase-2 to Phase-3. The hydrologically consistent area of the reservoir in the post-monsoon season was more stable than in the pre-monsoon season. Unchanged hydrological consistency areas were respectively 211.33 km<sup>2</sup> and 202.56 km<sup>2</sup>. From the hydrological consistency change matrix, it was clear that over time, the transformation of consistency from higher to lower is about 10.62 km<sup>2</sup> and 51.97 km<sup>2</sup> in the post-monsoon season. Only 36.65 km<sup>2</sup> area noticed positive changes in the hydrological consistency category between Phase-1 to Phase-2. No significant evidence was found indicating any improvement in hydrological consistency from Phase-2 to Phase-3. Figure 8 displays the areal transformation (in percentage) of hydrological consistency classes for pre- and post-monsoon seasons. These transformations in hydrological consistency are likely to have a substantial impact

on the ecological efficiency and overall health of the reservoir's ecosystem.

## 5.6 Relative water depth dynamics of Pong reservoir

Figure 9 illustrates the dynamics of relative water depth over the different phases. The relative water depth of the reservoir was analysed based on the change of MNDWI intensity over the reservoir. The fluctuation of MNDWI intensity serves as a critical indicator of the reservoir ecosystem's health. Figure 9 shows that in Phase-3 (2015–2024), the average MNDWI score was reduced to 0.15 from 0.39 in the pre-monsoon season. This reduction in MNDWI intensity indicates a qualitative degradation of the wetland concerning water thickness. Conversely, an increase in MNDWI intensity would signify an improvement in the water depth. The result also stated that for the post-monsoon season,



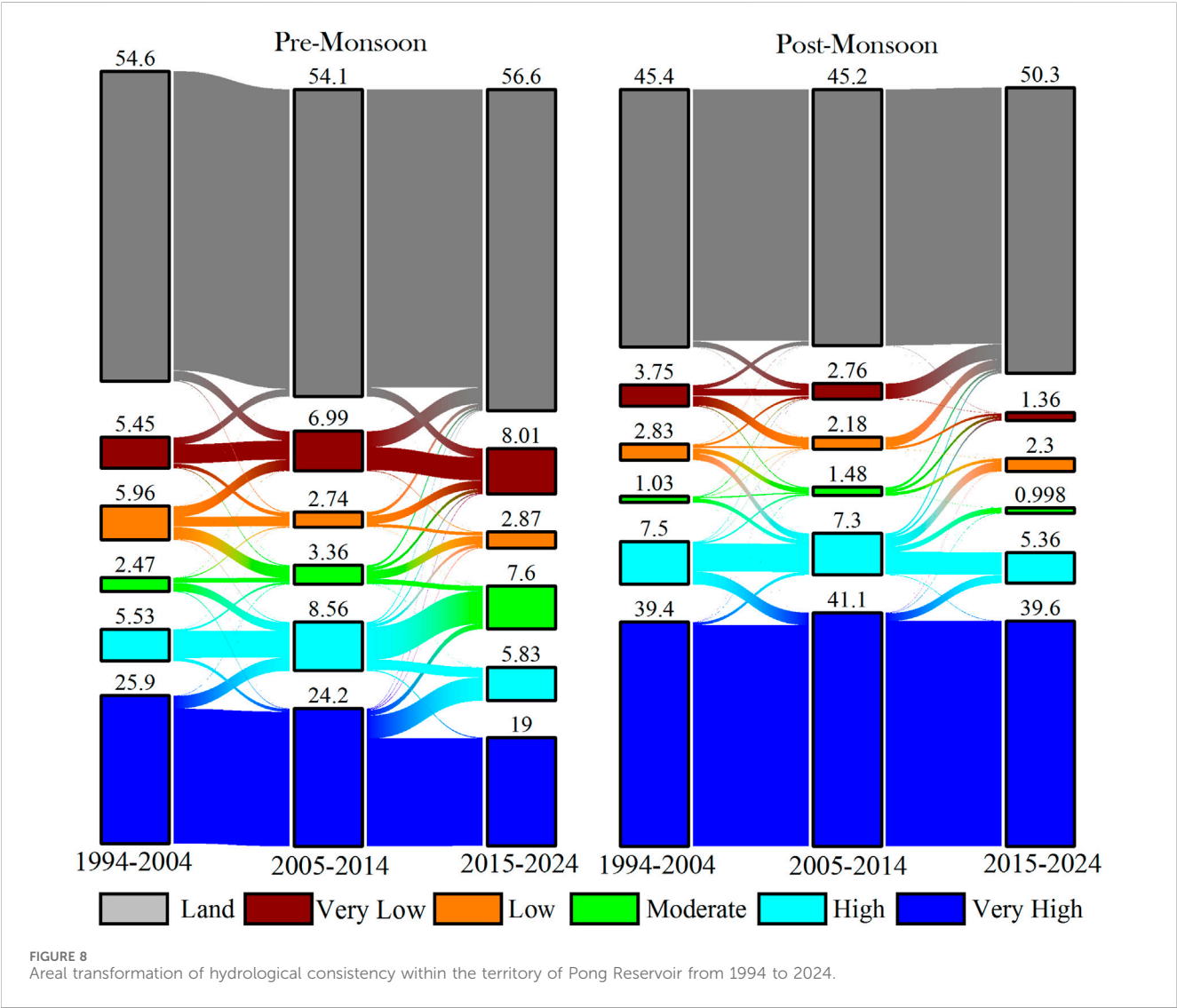
TABLE 7 Areal extent of changes in hydrological consistency characters of pre-and post monsoon seasons.

| Category             | Changes in HC classes  | Pre-monsoon                 |                             | Post-monsoon                |                             |
|----------------------|------------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
|                      |                        | From 1994–2004 to 2005–2014 | From 2005–2014 to 2015–2024 | From 1994–2004 to 2005–2014 | From 2005–2014 to 2015–2024 |
|                      |                        | Area in sq km               | Area in sq km               | Area in sq km               | Area in sq km               |
| Unchanged            | Land to Land           | 245.46                      | 244.29                      | 206.28                      | 209.79                      |
|                      | Very Low to Very Low   | 15.50                       | 18.88                       | 5.58                        | 0.18                        |
|                      | Low to Low             | 8.01                        | 2.57                        | 1.5                         | 0.08                        |
|                      | Moderate to Moderate   | 3.42                        | 3.96                        | 0.81                        | 0.05                        |
|                      | High to High           | 21.66                       | 8.01                        | 22.69                       | 18.25                       |
|                      | Very High to Very High | 109.65                      | 87.79                       | 180.75                      | 184                         |
| Changes in Very High | Very High to Land      | 0.00                        | 0.33                        | 0                           | 0.01                        |
|                      | Very High to Very Low  | 0.00                        | 0.44                        | 0.02                        | 0.02                        |
|                      | Very High to Low       | 0.01                        | 0.61                        | 0.1                         | 0.23                        |
|                      | Very High to Moderate  | 0.22                        | 4.42                        | 0.14                        | 0.22                        |
|                      | Very High to High      | 10.66                       | 18.99                       | 2.36                        | 6.64                        |
| Changes in High      | High to Land           | 0.00                        | 0.71                        | 0.01                        | 1.5                         |
|                      | High to Very Low       | 0.01                        | 1.01                        | 0.27                        | 1.66                        |
|                      | High to Low            | 0.13                        | 2.52                        | 0.37                        | 7.87                        |
|                      | High to Moderate       | 1.42                        | 26.84                       | 1.18                        | 4.36                        |
|                      | High to Very High      | 2.51                        | 0.69                        | 10.36                       | 0.29                        |
| Changes in Moderate  | Moderate to Land       | 0.00                        | 1.80                        | 0.04                        | 2.01                        |
|                      | Moderate to Very Low   | 0.13                        | 2.61                        | 0.46                        | 2.32                        |
|                      | Moderate to Low        | 0.70                        | 7.15                        | 0.26                        | 2.46                        |
|                      | Moderate to High       | 6.84                        | 0.10                        | 3.21                        | 0.01                        |
|                      | Moderate to Very High  | 0.39                        | 0.00                        | 0                           | 0                           |
| Changes in Low       | Low to Land            | 0.07                        | 3.080                       | 0.27                        | 8.09                        |
|                      | Low to Very Low        | 9.05                        | 6.984                       | 1.74                        | 1.95                        |
|                      | Low to Moderate        | 9.96                        | 0.086                       | 4.06                        | 0                           |
|                      | Low to High            | 0.61                        | 0.002                       | 5.59                        | 0                           |
|                      | Low to Very High       | 0.02                        | 0.001                       | 0                           | 0                           |
| Changes in Very Low  | Very Low to Land       | 6.11                        | 13.11                       | 3.4                         | 12.63                       |
|                      | Very Low to Low        | 3.17                        | 0.49                        | 7.7                         | 0.02                        |
|                      | Very Low to Moderate   | 0.56                        | 0.03                        | 0.67                        | 0                           |
|                      | Very Low to High       | 0.02                        | 0.01                        | 0.1                         | 0                           |

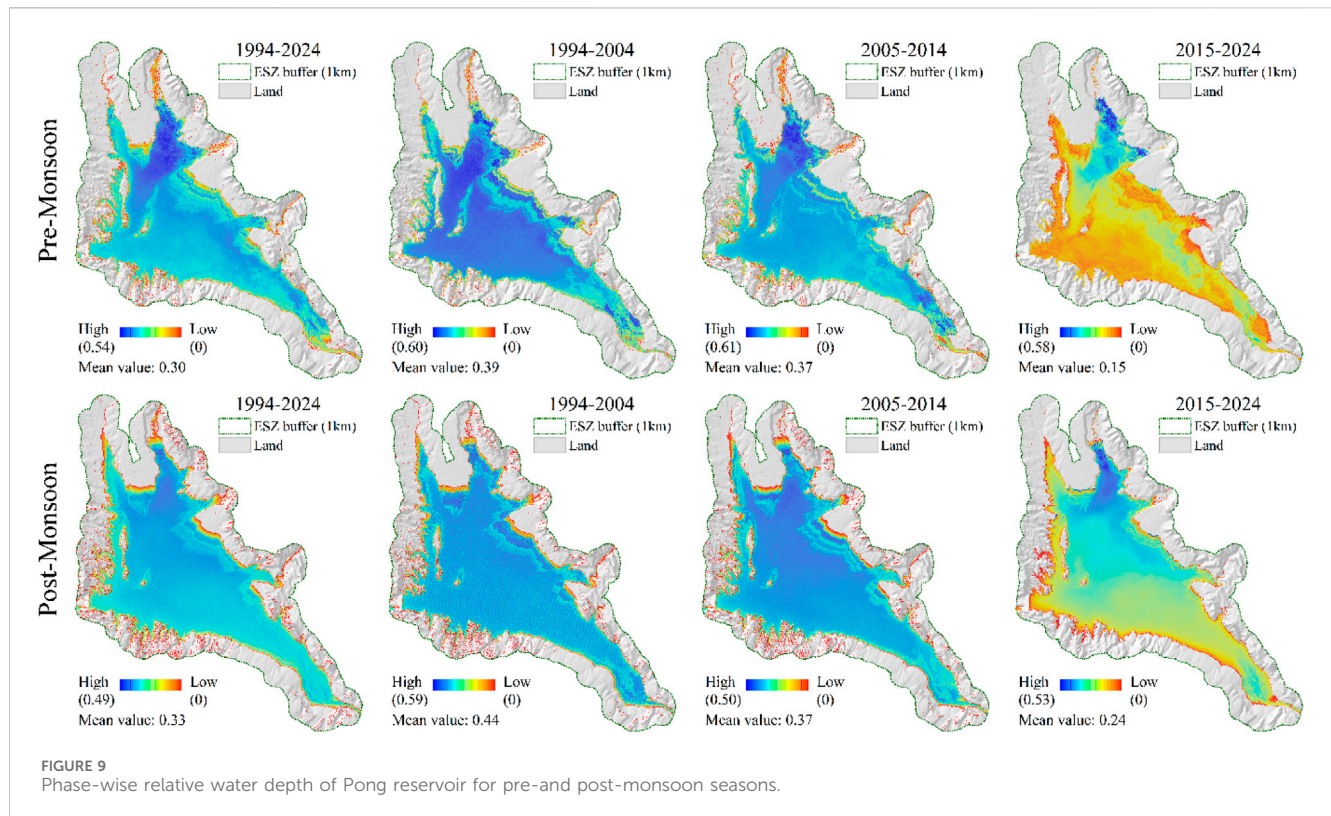
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TABLE 7 (Continued) Areal extent of changes in hydrological consistency characters of pre-and post monsoon seasons.

| Category           | Changes in HC classes | Pre-monsoon                 |                             | Post-monsoon                |                             |
|--------------------|-----------------------|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
|                    |                       | From 1994–2004 to 2005–2014 | From 2005–2014 to 2015–2024 | From 1994–2004 to 2005–2014 | From 2005–2014 to 2015–2024 |
|                    |                       | Area in sq km               | Area in sq km               | Area in sq km               | Area in sq km               |
|                    | Very Low to Very High | 0.00                        | 0.00                        | 0                           | 0                           |
| Land to HC classes | Land to Very Low      | 7.84                        | 7.33                        | 4.77                        | 0.2                         |
|                    | Land to Low           | 0.70                        | 0.02                        | 0.19                        | 0.02                        |
|                    | Land to Moderate      | 0.05                        | 0.01                        | 0                           | 0                           |
|                    | Land to High          | 0.00                        | 0                           | 0                           | 0                           |
|                    | Land to Very High     | 0.00                        | 0                           | 0                           | 0                           |



the average MNDWI score was 0.44 for the Phase-1 (1994–2004), but it was 0.24 in Phase 3 (2015–2024). This decline reflects a gradual reduction in water thickness, which negatively impacts the habitat quality. A spatial analysis of relative water depth also exhibited that in the Phase-3, a significant shallowing area was detected in the reservoir fringe area. Additionally, the effects of



temporal distance contribute to the hydrological deterioration of the reservoir.

## 5.7 Hydrological variability and trend in the relative water depth of the reservoir

Season-wise variability of reservoir water thickness was illustrated in Figures 10, 11. The coefficient of variation value (%) ranges from 156.99 to 173.70 for the pre-monsoon season and 163.86 to 186.64 for the post-monsoon season from 1994 to 2024. The reservoir fringe area experienced high variation in the relative water depth. Pixel-wise relative water depth images in the backwatered regions from 1994 to 2024 represent the spatial trend modelling, including the coefficient of determination ( $R^2$ ) and regression slope (b) for pre- and post-monsoon seasons displayed in Figures 10, 11. The trend analysis result revealed that the reservoir core part experienced a negative trend, and the value of the regression slope (b) varies from  $-0.02$  to  $0.01$ , with a coefficient of determination ( $R^2$ ) varying from  $0.74$  to  $0.85$  in the last 30 years (1994–2024) for pre- and post-monsoon seasons. This sort of finding indicates a decreasing trend over time and a quantitatively reduced relative water depth of the reservoir in both seasons. Figures 10, 11 also show the pixel-wise trend of relative water depth for pre- and post-monsoon seasons in different periods. In the 1st, 2nd, and 3rd phases, the computed coefficient of determination varied from  $0$  to  $0.92$ ,  $0$  to  $0.77$ , and  $0$  to  $0.89$  for the pre-monsoon season and  $0$  to  $0.94$ ,  $0$  to  $0.92$ , and  $0$  to  $0.92$  for the post-monsoon season. While the average value was  $0.45$  in Phase-1 (1994–2004), it stands at  $0.50$  in Phase-3

(2014–2024). It signifies the progressive trend in the degree of change. In addition to obtaining the direction of change, pixel-wise beta value (intercept) was computed for pre- and post-monsoon seasons (Figures 10, 11). From the figures, it was found that peripheral parts of the reservoir exhibited positive change in the pre-monsoon season, but this does not necessarily mean that the water body was stable. This situation happened because it was a transitional part of the reservoir. The core part of the reservoir shows a negative change during the pre-monsoon season over the years, and it is not a good sign from the wetland preservation point of view. The result suggests that the shallow water levels in backwaters were increasing, alongside a growing water scarcity during the pre-monsoon season. The result further indicates that the intensity of waterlogging depth has changed significantly in the reservoir areas due to anthropogenic and natural factors. Various particles (organic and inorganic) were carried down and deposited along the riverbed. Over time, these particles accumulated in the reservoir area and caused a continuous decrease in its depth. As a result, the water storage capacity was adversely affected.

## 6 Discussion

The monitoring of hydrological dynamics in the Pong reservoir revealed a reduction in the water cover area and a decline in the hydrological consistency character over time. The study also recorded seasonal variations in shallow water depth within the reservoir. The hydrological consistency of a reservoir is a complex interplay of several interacting factors, including sedimentation, rainfall, and river inflow. However, this study did not examine the role of water inflow into the



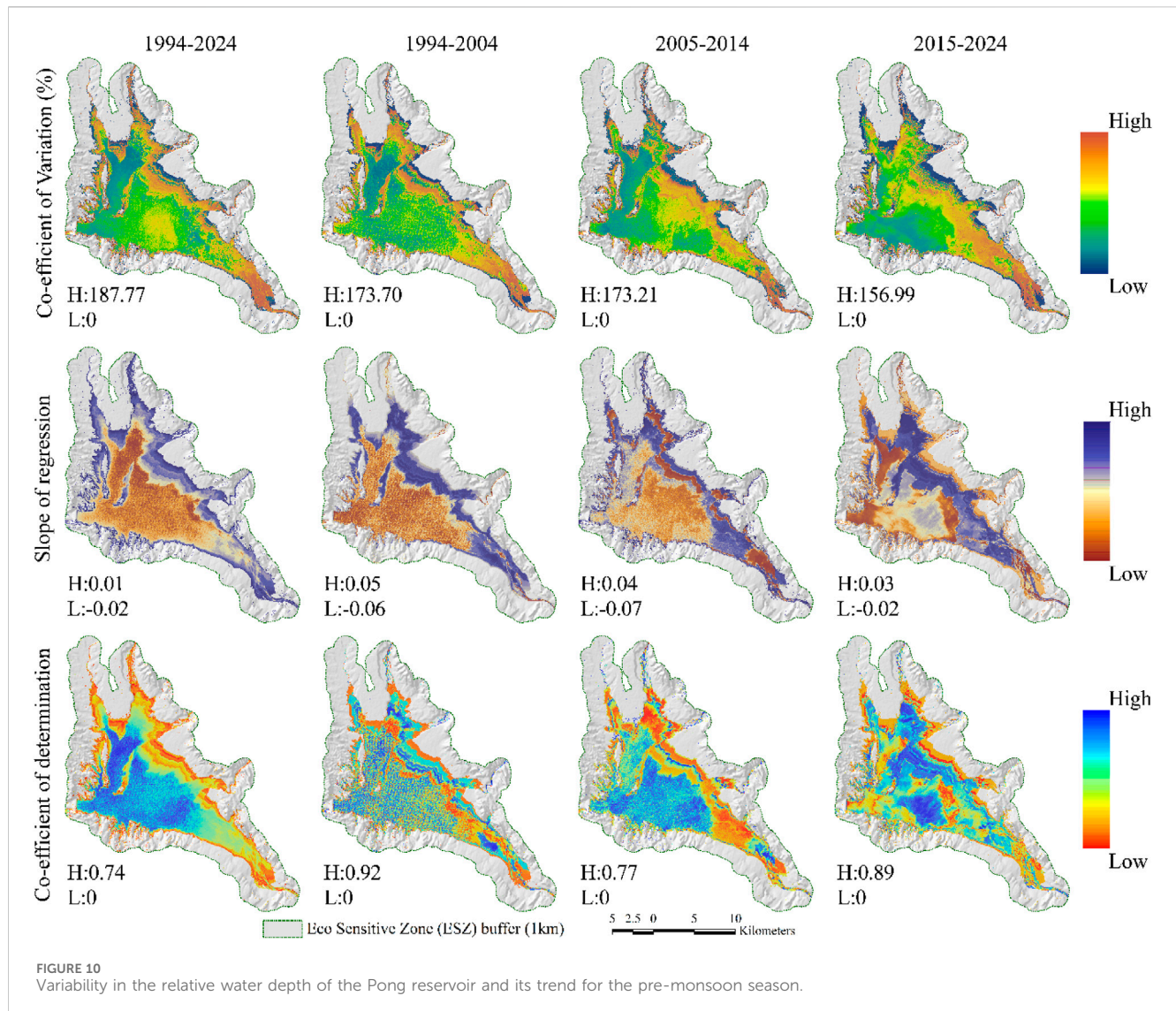


FIGURE 10  
Variability in the relative water depth of the Pong reservoir and its trend for the pre-monsoon season.

reservoir, which remains a critical area for understanding the hydrological dynamics of the reservoir. It is crucial to highlight that the rainfall regime and its seasonal variability play a pivotal role in regulating water influx into the reservoir. Approximately 36.18 km<sup>2</sup> of the reservoir area was identified as seasonal. Seasonal variability in rainfall is the key factor driving the fluctuations in the water cover area from season to season. Therefore, the trend analysis was performed using linear regression to examine the temporal nature of the seasonal rainfall. For this examination, IMD-endorsed rainfall data (1994–2024) were utilized. This comprehensive dataset provides crucial historical rainfall records across various regions of India, enabling robust long-term trend assessment (Nandi et al., 2024). The result shows that there is no significant trend in the seasonal rainfall over Pong Reservoir (Table 8). Hence, the study extended the analysis to encompass different rainfall indices, which provides a comprehensive view of the rainfall regime of the region (Figure 12). The outcomes show statistically significant decreasing trends in the number of rainy days, maximum consecutive wet days, and total precipitation on wet days. These results suggest that rainfall occurred less frequently over the study period and trends towards shorter wet spells. Interestingly, indices related to

extreme rainfall events, such as heavy precipitation days (>64 mm), maximum 1-day rainfall, and maximum 5-day rainfall, did not show any statistically significant trend. These sorts of findings were treated as the major driving factor for reducing flow influx as reported in this present study, which can also contribute to the hydrological consistency of the reservoir. This indicates a complex and potentially unpredictable hydrological future for Pong Reservoir and its surrounding ecosystems.

Besides decreasing the rainfall trend, the reservoir faces challenges associated with sediment influx or escalating sediment deposition. This sedimentation not only obstructs the flow of water but also leads to a gradual decrease in the water depth of the reservoir. The overview of the regression model indicates that the intensity of water logging depth changed over the period (1994–2024). The core area of the reservoir exhibits a discernible trend of relative water depth. Previous literature also reported that gradual siltation of the reservoir bed and loss of water retaining capacity of the same were ensuing problems for the Pong reservoir (Garg and Jothiprakash, 2013; Shukla et al., 2017; Sharma et al., 2021). This sort of finding was further supported by the trend of siltation rate and gross storage of reservoirs in past years based on

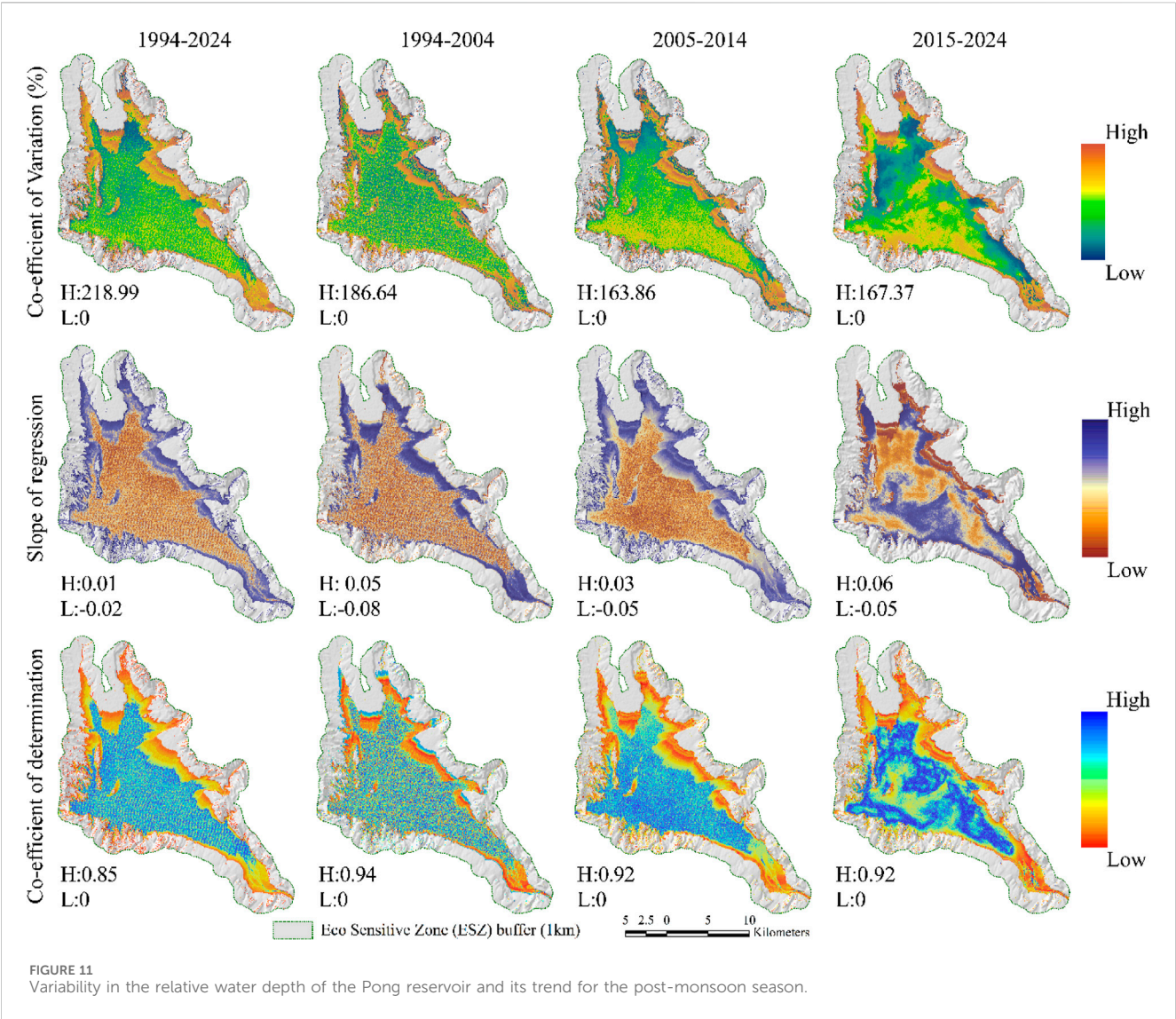


TABLE 8 Seasonal rainfall statistics and their trend over the Pong reservoir.

| Season       | Mean rainfall (mm) | Standard deviation | Coefficient of variation (%) | Regression equation | R <sup>2</sup> | Remarks       |
|--------------|--------------------|--------------------|------------------------------|---------------------|----------------|---------------|
| (1994–2024)  |                    |                    |                              |                     |                |               |
| Pre-monsoon  | 52.99              | 27.17              | 51.27                        | y = 0.105x – 159.5  | 0.001          | Insignificant |
| Monsoon      | 297.84             | 95.51              | 32.07                        | y = –3.546x + 7423. | 0.114          | Insignificant |
| Post-monsoon | 21.95              | 18.79              | 85.59                        | y = 0.094x – 167.6  | 0.002          | Insignificant |
| Winter       | 71.59              | 42.76              | 59.74                        | y = –0.470x + 1016. | 0.010          | Insignificant |

the data received from the India WRIS platform. The positive trend of siltation rate ( $y = 0.0338x + 1.2718$ ;  $R^2 = 0.21$ ) and a negative trend of gross storage area ( $y = -23.546x + 8049.1$ ;  $R^2 = 0.94$ ) of the reservoir explain the squeeze of relative water depth of the reservoir over the years (1994–2018). The increased siltation rate affects the gross storage of the reservoir, aligning with the previous research by Shukla et al. (2017) and Malik and Rai (2019). They also reported that the rate of sedimentation (varies from 18.08 to 24.40 Mm<sup>3</sup>/year)

of the Pong reservoir was gradually increasing, which would also lead to a gradual decrease in maximum water depth. This sort of finding signifies the declining trend of water storage, which is against of economic interests of the people. On the other side, changes in water depth can also affect the habitat availability for aquatic life and potentially lead to adverse effects on the local ecosystem.

As the depth of the reservoir continues to decrease, there will be a chance of an extension of the water presence area within the



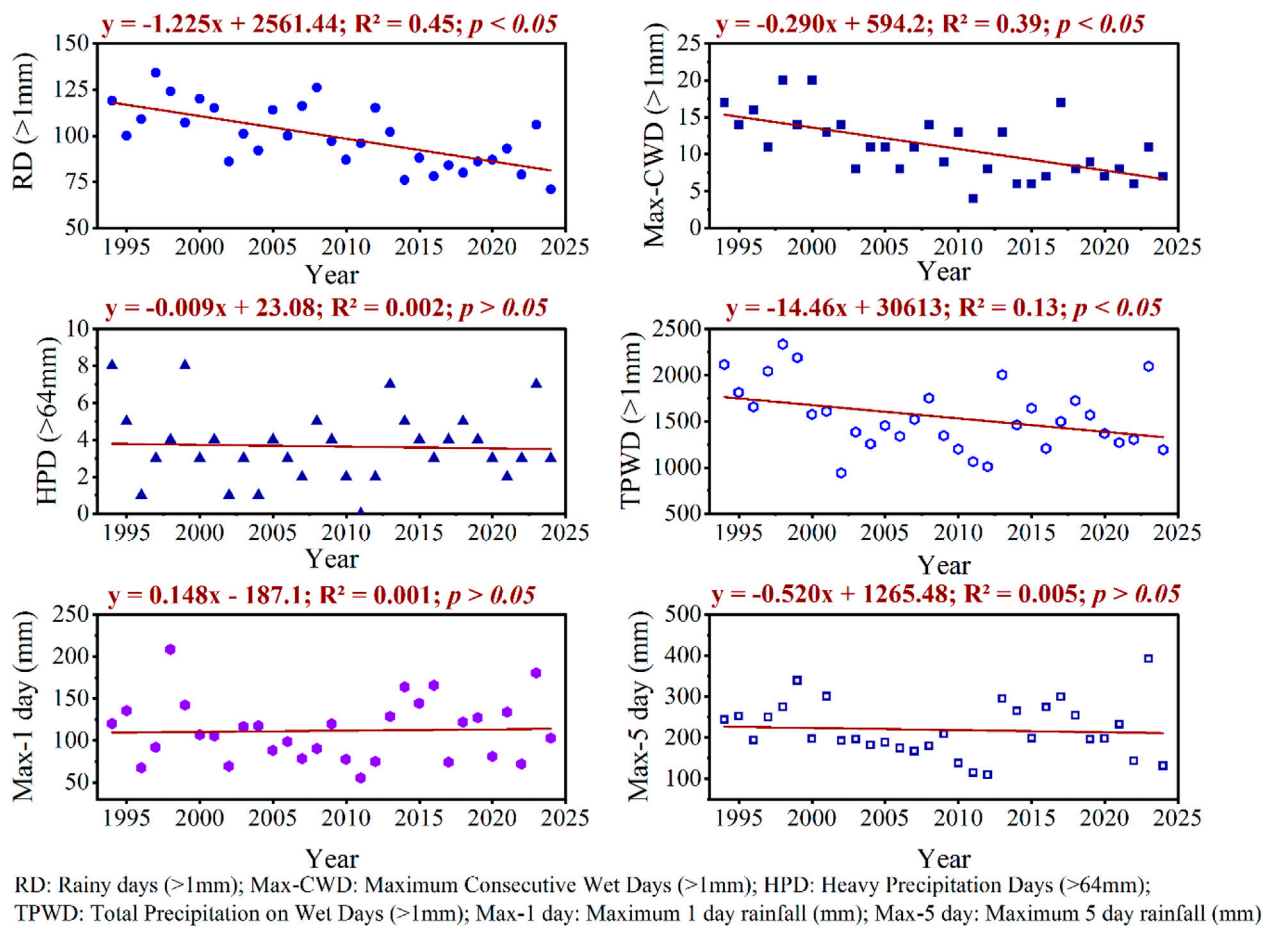


FIGURE 12  
Trend result of different rainfall indices across Pong reservoir from 1994 to 2024.

reservoir. The outcome of this research work is almost identical to the above-stated theoretical expectation because in the post-monsoon season water cover area remained relatively stable, but a significant reduction was observed in the reservoir water depth. In the regions where hydrological data is limited and time-series inflow statistics are not available, this approach is very useful for monitoring the hydrological conditions of the reservoir. While there are positive aspects to this work, it is also important to mention some limitations that must be addressed in future studies. Firstly, due to the lack of cloud-free images, the monsoon months were not taken in this analysis. Secondly, the satellite data used in this study has relatively coarser spatial resolution. So, future studies in this direction should use higher resolution images. Thirdly, instead of using the spectral index score as a proxy for relative water depth, calibrating water depth could enhance the scientific validity of this analysis. This research work effectively quantified the spatial and temporal reduction in hydrological consistency and water depth. However, since it relied exclusively on remote sensing data, it did not provide direct quantitative measurements of the underlying causal factors, such as sediment load or the rate of reservoir siltation. Therefore, future research should aim to integrate these observations in the inference of the drivers of hydrological degradation. Inflow and

outflow monitoring would be another approach that could be incorporated into further research work and strengthen the robustness of these findings.

## 7 Conclusion

The present study investigated the hydrological characteristics of a Ramsar-designated wetland site through time series monitoring of satellite images. Among the three water extraction techniques employed, the Modified Normalized Difference Water Index (MNDWI) was found to be the most effective. This research analyzed dual-season monitoring of hydrological characteristics, including hydrological consistency and trends in relative water depth within the reservoir. The findings indicate that the area of consistent water cover has decreased over the past 30 years (1994–2024) during both pre- and post-monsoon seasons. Additionally, qualitative degradation in the hydrological consistency area is particularly pronounced in the fringe regions of the reservoir, highlighting an emerging threat to both ecosystem stability and ecological health. To address the challenge of limited *in-situ* data, this study utilized spectral water indices to estimate the relative water depth of the reservoir. It provided a comprehensive

spatio-temporal analysis of reservoir water dynamics. The results show a decreasing trend in the core area of the reservoir over time, along with a quantitatively reduced relative water depth in both the pre- and post-monsoon seasons. These trends are likely caused by a combination of factors, such as shorter wet spells and sedimentation, which are concerning indicators of habitat degradation and ecosystem loss. The findings provide the essential geospatial intelligence for developing a resilient and effective management plan that is crucial for upholding the ecological character and ensuring the long-term sustainability of the Ramsar designation. The analysis of spatial changes in hydrological consistency offers valuable insights that allow for early identification of water storage vulnerabilities. This highlights the need for proactive management strategies, such as prioritizing conservation zones and implementing adaptive water release schedules. Additionally, the use of satellite imagery is particularly effective in infrastructure-scarce conditions for measuring and monitoring reservoir water dynamics. Therefore, the study recommends applying this approach to other reservoirs to enhance water resource management and improve drought monitoring efforts.

## Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: <https://earthexplorer.usgs.gov>.

## Author contributions

RS: Methodology, Writing – original draft, Formal Analysis, Software, Data curation, Resources, Conceptualization, Writing – review and editing. PK: Methodology, Validation, Conceptualization, Supervision, Writing – review and editing, Resources.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/frsen.2025.1682140/full#supplementary-material>

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