

Article

Spatiotemporal Dynamics of Dongting Lake During the Flood Season Using Long Time Series SAR Imagery on Google Earth Engine

Wei Li ^{1,2,3,†}, Liangyu Chen ^{4,†}, Yunfei Zhang ⁴, Bing Sui ^{1,2,3,*}, Dongsheng Du ^{1,2,3}, Yu Han ^{1,2,3} and Leishi Chen ^{1,2,3}

¹ Hunan Key Laboratory of Meteorological Disaster Prevention and Reduction, Changsha 410118, China; liwei163104@163.com (W.L.); windrisingdl@163.com (D.D.); shmilly1997@gmail.com (Y.H.); chenleishi0917@gmail.com (L.C.)

² Hunan Institute of Meteorological Sciences, Changsha 410118, China

³ Dongting Lake National Climate Observatory, Yueyang 414000, China

⁴ School of Aeronautical Engineering, Changsha University of Science & Technology, Changsha 410114, China; chenly717@csust.edu.cn (L.C.); zhang.yunfei@csust.edu.cn (Y.Z.)

* Correspondence: sui_bing@163.com

† These authors contributed equally to this work.

Highlights

What are the main findings?

- A novel SAR-based water extraction framework was developed, integrating Genetic Algorithm-optimized adaptive thresholding with dynamic morphological refinement for flood-season mapping.
- The framework effectively suppresses interference from sediment turbidity, exposed mudflats, and seasonal vegetation, ensuring high accuracy under complex hydrological conditions.

What are the implications of the main findings?

- The proposed framework facilitates ungauged water-level estimation, flood-risk identification, and sustainable water-resource management in large lake basins.
- This study provides a transferable approach for spatiotemporal hydrodynamic analysis and climate-response assessment of inland water systems using multi-source remote sensing.

Abstract

Flood-season lake spatiotemporal dynamics are vital for ecological security and socioeconomic development, requiring consistent high-resolution monitoring. However, precipitation fluctuations and sediment turbidity significantly alter water quality, while blurred boundaries between water and floodplain wetlands challenge precise monitoring. To address these issues, this study proposes a water body extraction method leveraging polarimetric Synthetic Aperture Radar data, utilizes the maximum between-class variance algorithm for initial segmentation, optimizes the threshold via a genetic algorithm, and employs dynamic morphological operations to refine boundary details. The method was validated using 2015–2025 Sentinel-1 flood-season time series of Dongting Lake on Google Earth Engine. The results demonstrate that the proposed method achieves stable and accurate water extraction across various years and seasons, with an overall accuracy surpassing 0.93, confirming its robustness and broad applicability. Furthermore, the spatiotemporal hydrodynamics and driving mechanisms of Dongting Lake were analyzed by

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integrating the extracted water areas with multi-source data, including water level, precipitation, discharge, temperature, and sunshine duration. Findings indicate that the flood-season water area exhibited a fluctuating trend, initially increasing and subsequently decreasing, peaking at 2202.26 km² in 2020 and dropping to 614.04 km² in 2025, a pattern primarily driven by extreme meteorological events such as heavy rainfall and prolonged droughts. Spatially, inundation patterns were characterized by deeper water in the north and shallower depths in the south, separated by a topographically higher central region. Regression analysis revealed a robust correlation between water area and water level with an R^2 of 0.931, providing a quantitative reference for water level estimation in ungauged regions. Additionally, discharge and precipitation were positively correlated with water area, whereas temperature and sunshine duration exerted a negligible influence. This study supports flood regulation in the Dongting Lake basin and provides a robust framework for analyzing lake dynamics using long-term SAR data.

Keywords: spatiotemporal dynamics; flood season; water body extraction; Dongting Lake; driving mechanisms

1. Introduction

Lakes are critical water resources that maintain ecological equilibrium and sustain socio-economic development [1,2]. Recently, the escalating frequency of extreme weather events has intensified the risk of lake-induced flooding, posing significant challenges to regional ecological security [3]. Dongting Lake, a major flood-regulation basin in the middle reaches of the Yangtze River, performs a pivotal role in disaster mitigation [4]. Consequently, long-term remote sensing monitoring of its flood-season spatiotemporal dynamics is imperative for optimizing flood management and elucidating the complex hydrological processes of the Yangtze River basin [5].

Remote sensing imagery, characterized by rapid acquisition, high temporal resolution, and extensive spatial coverage, has become a fundamental data source for water body extraction [6,7]. Methodologies in this domain are typically categorized into optical-based, Synthetic Aperture Radar (SAR)-based, and multi-source fusion approaches. Optical methods primarily leverage spectral reflectance contrasts, specifically the high absorption of water in the NIR and SWIR regions. Common techniques include single-band thresholding, spectral mixture analysis, and multi-band indices. For instance, Ji et al. [8] demonstrated that the NDWI calculated as $(\text{Green} - \text{SWIR})/(\text{Green} + \text{SWIR})$, where SWIR represents the shorter wavelength region, exhibits the most stable threshold. Similarly, Ouma et al. [9] developed a hybrid water index merging Tasseled Cap Wetness and the Normalized Difference Water Index, a logical integration employed to quantify hydrological dynamics across five saline and non-saline Rift Valley lakes in Kenya. Goffi et al. [10] combined spectral indices with Hue-Saturation-Value (HSV) features using Ordered Weighted Averaging (OWA) to develop a parameter-free flood mapping framework, achieving high accuracy and robustness. To mitigate interference from terrain shadows and high turbidity, Farhadi et al. [11] introduced the Flood/Water Body Extraction Index (FWEI), effectively reducing omission errors in heterogeneous scenes.

Under adverse weather conditions, such as persistent cloud cover and heavy precipitation, the utility of optical remote sensing is severely limited by its inability to penetrate the atmosphere and acquire surface information [12]. In contrast, Synthetic Aperture Radar (SAR), an active microwave sensing technology, is independent of solar illumination and weather conditions, enabling all-weather and all-day observations. Consequently, SAR serves as a critical tool for real-time monitoring during flood events [13]. SAR-based

water extraction primarily leverages the distinct microwave backscattering signatures of various land cover types, with methodologies typically categorized into single-polarization [14] and dual-polarization approaches [15]. For example, Binh et al. [16] integrated Sentinel-1 VH and VV features using a neural network to monitor surface water in the Mekong region, while Liang et al. [17] developed a local thresholding method that combines VV and VH segmentation to delineate water boundaries accurately. Despite these advantages, SAR imagery remains susceptible to radar shadows and speckle noise, which can constrain mapping precision. To mitigate these limitations, fusion strategies integrating optical and SAR data have been developed to overcome single-source deficiencies and improve result reliability. Hong et al. [18] refined SAR water extraction thresholds using preliminary land-use maps derived from Landsat imagery within an object-based classification framework. Similarly, Tian et al. [19] coupled SAR backscatter coefficients with the optical Normalized Difference Water Index (NDWI) to construct the SAR and Optical Imagery Water Index (SOWI), achieving high-precision water extraction across diverse scenarios and demonstrating its efficacy in monitoring the Henan flood disaster.

Traditional lake extraction methods generally rely on sparse imagery within limited temporal windows, which fails to satisfy the demand for long-term dynamic monitoring. These approaches often suffer from poor temporal continuity and low computational efficiency when processing large-scale geospatial datasets [20,21]. Recently, Google Earth Engine (GEE), characterized by its high-performance parallel processing capabilities, has become a cornerstone for regional and global research [22], facilitating significant advancements in long-term lake dynamics monitoring [23]. For instance, Zhou et al. [24] utilized GEE and multi-decadal Landsat archives to achieve the first 27-year continuous monitoring (1991–2017) of lakes on the Mongolian Plateau. Their work elucidated phased change patterns and driving mechanisms. Wang et al. [25] developed multi-index water detection rules to efficiently map the Dongting Lake extent over 34 years (1987–2020), identifying pronounced “summer expansion and winter contraction” seasonality alongside a persistent shrinkage in permanent water area. Furthermore, a dual-algorithm framework integrating “histogram segmentation” and “temporal filtering” on GEE was applied to Sentinel-1 SAR data. This framework enabled high-frequency flood monitoring of Poyang and Dongting Lakes over five years. To our knowledge, it is the first to quantify systematic flood-frequency estimation discrepancies among multi-source datasets [26]. More recently, Chen et al. [27] introduced the AWL-LSTM deep learning model, which incorporates hydrological mechanisms. The model couples GEE-derived area time series with in situ water levels to optimize the loss function, significantly enhancing prediction accuracy across heterogeneous hydrological stages.

Global warming has intensified hydrological imbalances, leading to more pronounced “summer flood and winter drought” fluctuations in inland lakes. The increasing frequency of extreme summer rainfall and extended flood durations have substantially elevated flood risks [28]. During these periods, lake spatiotemporal dynamics become highly volatile, with rapid variations in area and stage. These variations disrupt natural hydrological cycles [29], diminish regulation capacity [30], and increase the complexity of disaster mitigation [31]. Despite these impacts, research specifically targeting long-term flood-season dynamics remains sparse, constrained by insufficient temporal depth [32] and a lack of rigorous spatiotemporal feature analysis [33].

To address these gaps, this study focuses on Dongting Lake, the second-largest freshwater lake in China. Exploiting the all-weather advantages of SAR data, we propose a water extraction method based on Sentinel-1 polarimetric data. The methodology integrates the Otsu maximum between-class variance algorithm with a genetic algorithm for adaptive threshold optimization, while incorporating dynamic morphological operators to refine boundary delineation and mitigate interference from mudflats and vegetation.

Utilizing the GEE platform and supplemented by high-resolution GF-3 imagery, we constructed a decadal dataset of Dongting Lake's flood-season (April–September) water dynamics from 2015 to 2025. This dataset facilitates a systematic analysis of temporal area evolution, spatial inundation frequency patterns, and the underlying climatic and hydrological drivers. Specifically, the response of lake volume to precipitation, discharge, temperature, and sunshine duration is examined. These findings provide a scientific basis for flood-season water resource management and offer a robust framework for applying long-term SAR time series in lake dynamics research.

2. Materials and Methods

2.1. Study Area

Dongting Lake (28°30'N–30°20'N, 110°40'E–113°10'E), situated on the southern bank of the middle Yangtze River, is China's second-largest freshwater lake, encompassing a basin area of approximately $26.14 \times 10^4 \text{ km}^2$. The lake's geographic setting is illustrated in Figure 1. Characterized by a topography that descends from west to east, the basin comprises East, South, and West Dongting, collectively forming a complex dish-shaped morphological structure. As a pivotal regulation and storage hub for the middle and lower Yangtze reaches, Dongting Lake serves a critical function during the flood season by sequestering floodwaters, buffering discharge fluctuations from the middle reaches, and managing regional water resources. Controlled by a subtropical monsoon climate, the lake's hydrological regime exhibits a distinct “rising-high-receding” pattern. Inflows are primarily supplied by the “Four Rivers” (Xiang, Zi, Yuan, and Li) from the west and south, which then discharge into the Yangtze River through the northeastern outlet at Chenglingji. Water levels typically begin to rise in April and May, peak from June to August, and gradually recede in September as upstream inflows decrease.

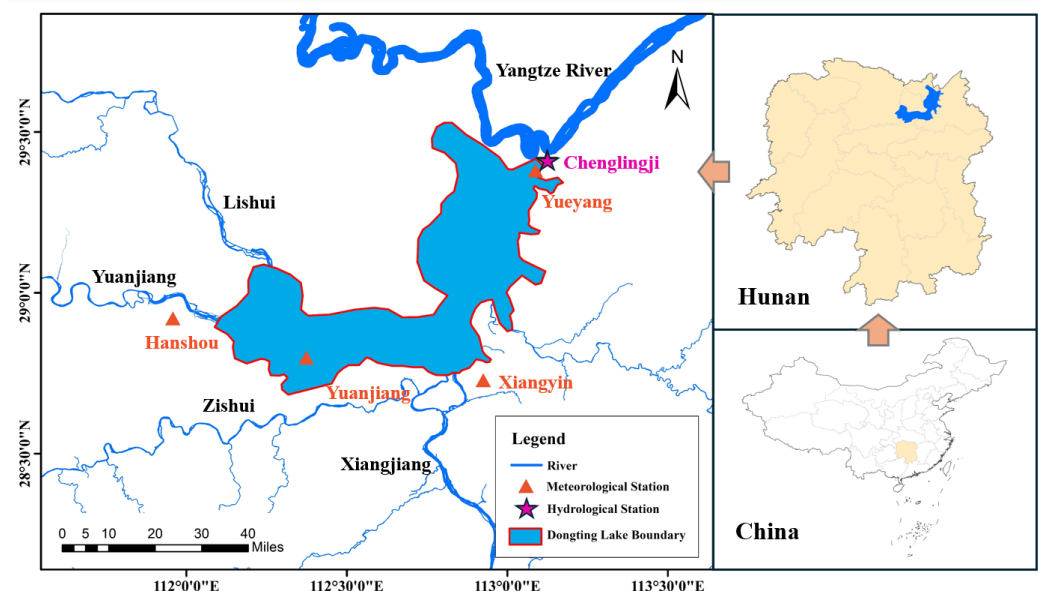


Figure 1. Location of the study area.

2.2. Experimental Data

This study utilized multi-source datasets to analyze the spatiotemporal dynamics of Dongting Lake during the flood season, including SAR imagery, optical imagery, water level, flow rate, precipitation, air temperature, and sunshine duration. The specific data applications are as follows: (1) long-term Sentinel-1 and GF-3 SAR archives were employed for water body extraction; (2) Sentinel-2 optical imagery served as the validation

reference for extraction results; (3) in situ water level records from hydrological stations were used to analyze lake variations; and (4) discharge, air temperature, sunshine duration, and basin-wide precipitation data were utilized to investigate the driving mechanisms of flood events.

2.2.1. Long Time Series SAR Data

Sentinel-1, a C-band Synthetic Aperture Radar (SAR) constellation developed by the European Space Agency (ESA), provides all-weather, day-and-night imaging, which is highly advantageous for surface water detection. The constellation consists of Sentinel-1A (launched in 2014, currently operational), Sentinel-1B (launched in 2016, decommissioned in 2022), and Sentinel-1C (launched in 2024 to restore dual-satellite capacity). In this study, 65 Sentinel-1 scenes covering the Dongting Lake region during the flood seasons (April–September) from 2015 to 2025 were selected. Dual-satellite Sentinel-1A/1B data were utilized for the 2015–2022 period, while Sentinel-1A single-satellite acquisitions were used for 2023–2025. All datasets were retrieved from the Copernicus Open Access Hub (<https://browser.dataspace.copernicus.eu/>, accessed on 1 April 2026). To bridge the identified temporal coverage gaps in June 2020, June 2021, July 2022, July 2024, and April 2025, Fine Strip images from China’s GaoFen-3 (GF-3) constellation (GF3-01, GF3-02, and GF3-03) were employed as supplementary data, selected for their consistent C-band and dual-polarization (VV/VH) mode. Following a standardized preprocessing workflow, including radiometric calibration, speckle filtering, terrain correction, conversion to backscatter coefficients (σ^0), reprojection, and resampling to a spatial resolution of 10 m, the Sentinel-1 and GF-3 datasets were harmonized to reduce potential sensor-induced inconsistencies. GF-3 images accounted for only 11% of the total dataset and were used exclusively to fill temporal gaps. Moreover, these images were distributed across different years rather than concentrated within a specific period. Given their limited proportion and the harmonized preprocessing procedure, any residual cross-sensor differences are unlikely to significantly affect the extracted water extent or the observed long-term trends. The spatiotemporal distribution of the SAR datasets used in this study is illustrated in Figure 2.

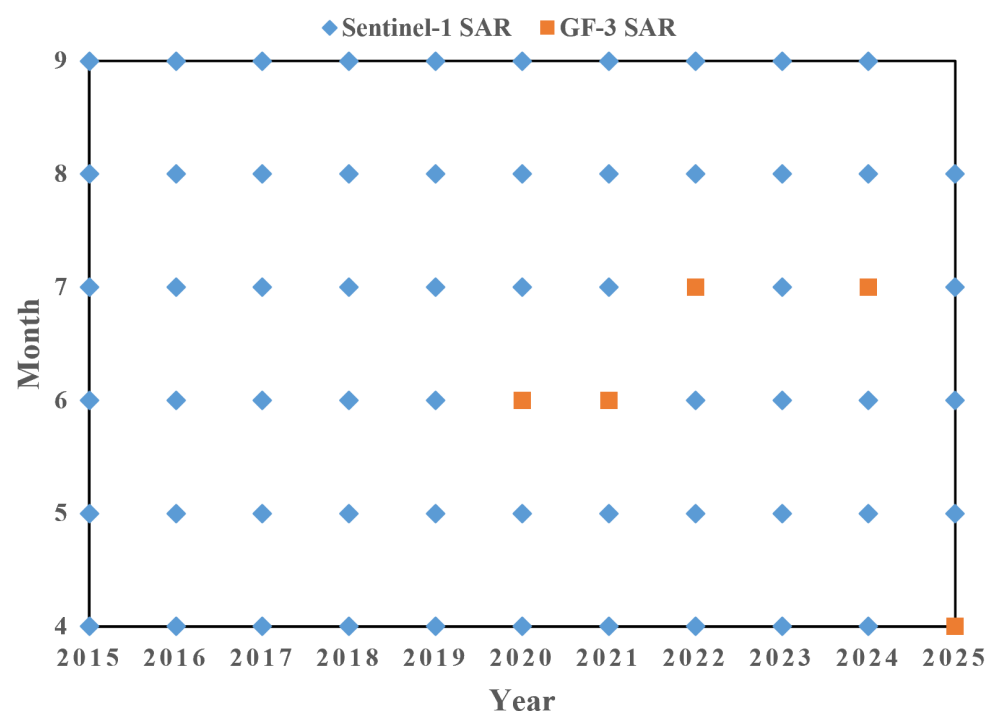


Figure 2. Distribution of SAR data used during the flood season in the study area.

2.2.2. Optical Image Data

The Sentinel-2 mission, a cornerstone of the European Space Agency (ESA) Copernicus program, is an optical satellite constellation designed for high-resolution terrestrial observation. The constellation comprises Sentinel-2A (launched in 2015), Sentinel-2B (launched in 2017), and Sentinel-2C (launched in 2024). Each platform carries a Multispectral Instrument (MSI) providing 13 spectral bands across the visible, near-infrared (NIR), and shortwave infrared (SWIR) domains, with a spatial resolution of up to 10 m, a 290 km swath width, and a high-revisit frequency. To evaluate the accuracy of the SAR-based water extraction, five cloud-free images were selected, specifically from 7 April 2019; 30 June 2019; 30 August 2021; 19 September 2024; and 16 July 2025. All datasets were retrieved from the Copernicus Open Access Hub.

2.2.3. Hydrological Data

Hydrological records, including water level and discharge data, were obtained from the Hunan Hydrology Public Service Platform. Specifically, hourly in situ water level and discharge measurements from the Chenglingji hydrological station were collected for the 2015–2025 period, ensuring temporal synchronization with the corresponding SAR acquisitions.

2.2.4. Climate Data

Meteorological datasets employed in this study consist of precipitation, air temperature, and sunshine duration. Precipitation data were derived from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) product on the GEE platform (https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_DAILY, accessed on 1 April 2026). This dataset provides a daily temporal resolution and a spatial resolution of $0.05^\circ \times 0.05^\circ$. The selected temporal span covers the flood seasons (April–September) from 2015 to 2025, encompassing the entire Dongting Lake Basin.

Air temperature and sunshine duration data were collected from four meteorological stations surrounding Dongting Lake, namely Yueyang, Hanshou, Yuanjiang, and Xiangyin, and were obtained from the Hunan Hydrology Public Service Platform. In this study, the monthly mean temperature during the flood season was calculated as the average of these four stations, while the monthly sunshine duration was derived as the mean of the cumulative monthly sunshine hours across the stations.

2.3. Methodology

This study introduces a water surface area extraction algorithm optimized for Sentinel-1 polarimetric data. The workflow begins with the calculation of the Sentinel-1 Dual-Polarized Water Index (SDWI) [34], followed by initial water body segmentation using the Otsu maximum between-class variance method. To enhance the segmentation performance, a genetic algorithm (GA) was implemented to determine the optimal adaptive threshold. In the post-processing phase, dynamic morphological operations were applied to refine boundary information and mitigate the interference caused by blurred transitional zones between floodplain mudflats and terrestrial surfaces. Subsequently, a correlation analysis between the extracted water surface area and in situ water level data was conducted to assess the feasibility of estimating flood-season water levels. Furthermore, by integrating discharge data from the Chenglingji station, CHIRPS precipitation, and localized temperature and sunshine records, we established the relationships between lake area variations and basin-wide hydrological and climatic drivers. This approach facilitates a systematic analysis of the spatiotemporal evolution of Dongting Lake's water extent and its underlying driving mechanisms. The comprehensive workflow, illustrated in Figure 3,

encompasses remote sensing data preprocessing, water extraction procedures, and the analysis of spatiotemporal dynamics and influencing factors.

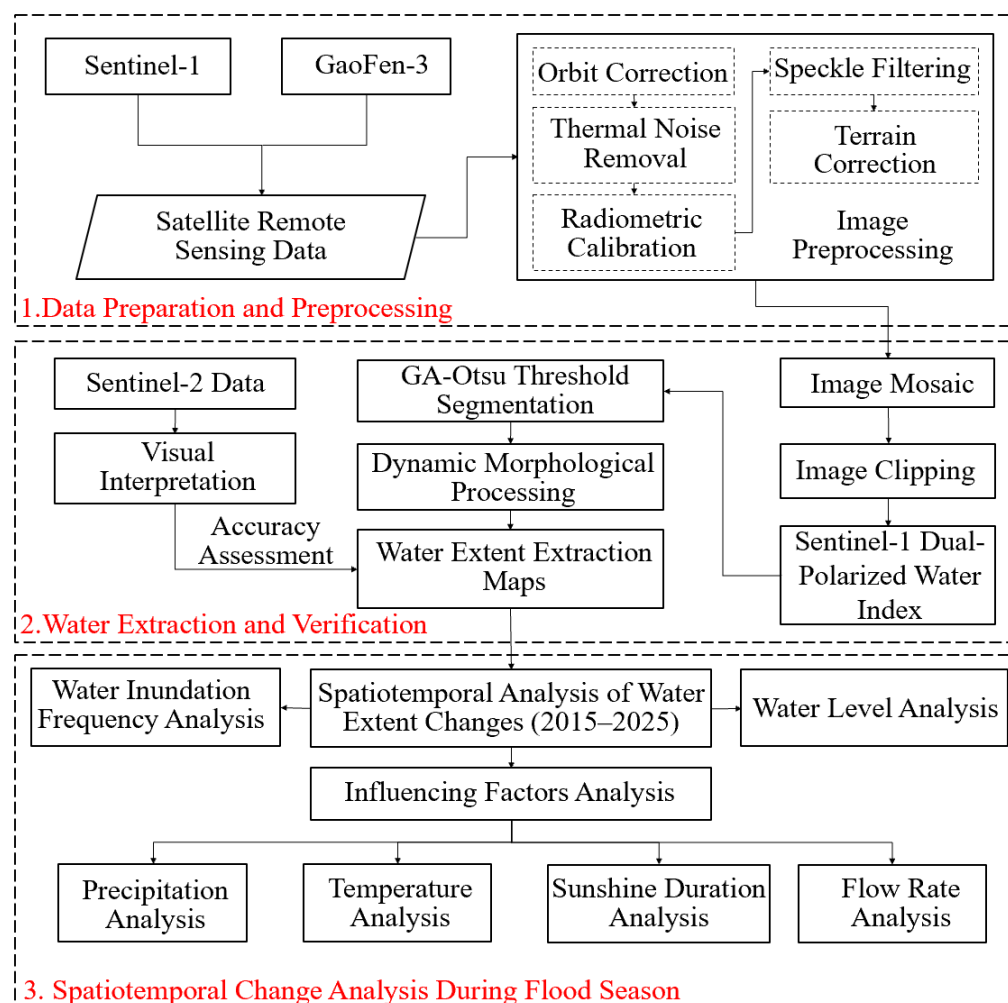


Figure 3. Overall methodological workflow: 1. data preparation and preprocessing, 2. Water extraction and verification, and 3. spatiotemporal change analysis during flood season.

2.3.1. Data Preprocessing

The data employed in this study consist of Sentinel-1 SAR Ground Range Detected (GRD) imagery. The preprocessing workflow, as illustrated in Figure 3, comprises the following steps: (1) orbit file application; (2) thermal noise removal; (3) radiometric calibration; (4) polarimetric speckle filtering; and (5) terrain correction using the Shuttle Radar Topography Mission (SRTM) 30 m Digital Elevation Model (DEM). The final products are dual-polarized VV and VH backscatter intensity data with a spatial resolution of 10 m. The dataset spans the flood seasons (April–September) from 2015 to 2025, encompassing 65 temporal acquisitions, thereby enabling high-spatiotemporal-resolution observations of Dongting Lake’s seasonal dynamics.

To bridge temporal gaps in Sentinel-1 acquisitions, five scenes of Gaofen-3 (GF-3) SAR imagery acquired in Quad-Polarization Stripmap (QPSI) mode were selected for June 2020, June 2021, July 2022, July 2024, and April 2025. Preprocessing for the GF-3 Level-1A data included multi-looking, speckle filtering, geocoding, and radiometric calibration, resulting in VV and VH dual-polarized imagery resampled to a 10 m spatial resolution.

Furthermore, Sentinel-2 optical imagery preprocessing involved atmospheric correction and spatial resampling. Atmospheric correction was performed using the Sen2Cor processor (European Space Agency, ESA) to convert Level-1C Top-of-Atmosphere (TOA)

reflectance to Level-2A Bottom-of-Atmosphere (BOA) reflectance. Resampling was conducted via the ESA Sentinel Application Platform (SNAP) to achieve a consistent 10 m spatial resolution across all bands.

To mitigate interference from saturated soil and riparian vegetation during the flood season, the preprocessed polarimetric data were used to calculate the Sentinel-1 Dual-Polarized Water Index (SDWI), which served as the primary feature for water body extraction. The SDWI is formulated as follows:

$$SDWI = \ln(10 \times VV \times VH) \quad (1)$$

where $SDWI$ denotes the water extraction index. Theoretically, pixels with $SDWI$ values greater than zero are classified as water bodies, whereas those with $SDWI$ values less than or equal to zero are identified as non-water bodies. Here, VV represents the SAR backscattering coefficient acquired in vertical transmit and vertical receive mode, while VH represents the backscattering coefficient acquired in vertical transmit and horizontal receive mode.

2.3.2. GA-OTSU Water Extraction Algorithm

This study employs a GA-Otsu threshold segmentation algorithm, which integrates the Genetic Algorithm (GA) [35] with the Otsu maximum between-class variance method [36], to segment the preprocessed $SDWI$ imagery. Threshold-based segmentation typically yields satisfactory results for remote sensing imagery with high radiometric contrast between water bodies and background features; thus, the Otsu algorithm was selected as the baseline approach. However, the exhaustive search mechanism of the standard Otsu method can be computationally intensive and may fail to identify the global optimal threshold in complex histograms, potentially leading to boundary blurring or loss of target details. To overcome these limitations, the Genetic Algorithm was incorporated into the Otsu framework to establish a more efficient and accurate GA-Otsu thresholding method. By leveraging the heuristic search capabilities of GA, this approach rapidly converges to the optimal threshold while effectively suppressing noise.

The maximum between-class variance principle is a classical segmentation technique particularly effective for images where the gray-level histograms of the foreground and background follow approximately normal distributions. Its core objective is to partition the image into two classes by maximizing the variance between them, thereby ensuring optimal separation between the target and the background. Assume that a remote sensing image has m gray levels, where the number of pixels with gray value i is denoted as n_i , and the total number of pixels is $N = \sum_{i=1}^m n_i$. The probability of each gray value is therefore given by $P_i = \frac{n_i}{N}$. By applying a threshold t , the image pixels can be divided into two groups, D_1 and D_2 , with probabilities f_1 and f_2 , and mean gray levels μ_1 and μ_2 , respectively. The corresponding formulas are as follows.

$$f_1 = \sum_{i=1}^t P_i \quad (2)$$

$$f_2 = \sum_{i=t+1}^m P_i = 1 - f_1 \quad (3)$$

$$\mu_1 = \frac{\sum_{i=1}^t (i \times P_i)}{f_1} = \frac{\mu(t)}{f(t)} \quad (4)$$

$$\mu_2 = \frac{\sum_{i=t+1}^m (i \times P_i)}{f_2} = \frac{\mu - \mu(t)}{1 - f(t)} \quad (5)$$

where $\mu = f_1 \times \mu_1 + f_2 \times \mu_2$ represents the mean gray level of the entire image. The between-class variance of D_1 and D_2 is calculated as follows:

$$\delta^2 = f_1(\mu_1 - \mu)^2 + f_2(\mu_2 - \mu)^2 \quad (6)$$

When δ^2 reaches its maximum, the corresponding threshold t^* is considered the optimal segmentation threshold. To enhance the segmentation performance of the Otsu algorithm and mitigate target detail loss and boundary blurring, a Genetic Algorithm (GA) was introduced to rapidly and accurately determine the optimal threshold. GA is a stochastic global optimization method that simulates natural selection processes, including replication, crossover, and mutation. In this study, an initial population of candidate solutions (chromosomes) is randomly generated. Parent individuals are selected via a selection operator, and offspring are produced through crossover and mutation operators to form subsequent generations. Superior individuals are iteratively screened based on the objective function and constraints to approach the global optimum. The basic framework of the Genetic Algorithm is illustrated as follows.

$$GA = (E, F, I, N, S, C, M, G) \quad (7)$$

where E denotes the encoding scheme of individuals; F represents the fitness evaluation function; I is the initial population; N indicates the population size; S is the selection operator; C denotes the crossover operator, with a crossover probability P_c typically ranging from 0.4 to 0.99; M represents the mutation operator, with a mutation probability P_m usually set between 0.0001 and 0.1; and G is the termination generation, generally set between 100 and 500.

In this study, a real-coded genetic algorithm was employed to optimize the Otsu threshold. F was defined as the between-class variance calculated according to the Otsu criterion, which quantifies the separability between water and non-water classes. I was randomly generated, and N was set to 50. S was implemented using a tournament selection strategy with a tournament size of three. C was performed with a crossover probability of 0.8, whereas M was applied with a mutation probability of 0.05 to introduce stochastic perturbations and maintain population diversity. In addition, two elite individuals were retained in each generation to prevent the loss of high-quality solutions. Unlike the traditional Otsu algorithm, GA-Otsu avoids exhaustive pixel probability calculations. By leveraging nonlinear optimization, it significantly enhances threshold determination speed while improving accuracy.

2.3.3. Dynamic Morphological Operation

Water bodies extracted using the GA-Otsu algorithm may still contain misclassifications, such as speckle noise, non-water “holes” within submerged areas, and discontinuities caused by topographic occlusions. Morphological post-processing is commonly employed to address these issues. However, traditional methods utilize structural elements (SE) of fixed shape and size. These static SE often fail to account for neighborhood spatial information, potentially leading to connectivity breakage or shape distortion in narrow, curved sections of complex river systems. Specifically, fixed SE may erroneously disconnect continuous water bodies in meandering channels or artificially expand boundaries in irregularly shaped water regions. To overcome these limitations, this study adopts an adaptive structural element construction method based on local pixel neighborhood density and symmetry [37]. The core idea is to determine whether a central pixel is a boundary point by analyzing the local density variance and directional symmetry within its neigh-

borhood. Based on this judgment, shape-adaptive SEs are constructed to maintain topological consistency, reduce information loss, and minimize distortion of fine boundary details.

The construction of adaptive structural elements is based on smoothing the neighborhood gray-level difference vector field. By defining a variation coefficient derived from local density and symmetry, the method determines the boundary status of the central pixel in a subregion and subsequently constructs the adaptive SE. The specific procedure is as follows. First, two masks, denoted as S (3×3) and M (5×5), are designed. Mask S is used to construct the adaptive SE, while mask M is used to analyze local neighborhood characteristics. Taking the original image pixel $f(4,4)$ as the center of S , a 3×3 subregion denoted as Q_S is selected; S is used to construct the adaptive structural element. Then, taking the first pixel in Q_S as the center of M , a 5×5 subregion denoted as Q_M is selected. The central pixel of Q_M is determined as a boundary point based on the variation coefficient defined from the local neighborhood density and symmetry of the pixel. Specifically, the variation coefficient F of the target pixel is defined as the ratio of the variance of the local density in its neighborhood to the neighborhood symmetry, as expressed by the following formula.

$$F = \frac{S_D}{S_Y + 1} \quad (8)$$

where S_D represents the variance of the local density in the neighborhood of the target pixel, which is calculated as follows,

$$S_D = \frac{\sum_{n \in C} [\rho(n) - \bar{\rho}(n)]^2}{N}, C = \{1, 2, \dots, N\} \quad (9)$$

$$\bar{\rho}(n) = \frac{\sum_{n \in C} \rho(n)}{N}, C = \{1, 2, \dots, N\}, \quad (10)$$

where $\bar{\rho}(n)$ denotes the mean local density of the target pixel's neighborhood, and n represents the number of pixels in the target pixel's neighborhood. S_Y represents the neighborhood symmetry of the target pixel, which is calculated as follows,

$$S_Y = \frac{\sum_{k=0}^4 \alpha |eq[f_k(i, j)] - ueq[f_k(i, j)]| + \beta}{2n} \quad (11)$$

where $f_k(i, j)$ denotes the gray value of the pixel in the k direction; $eq[\cdot]$ represents the number of pixels with the same gray value as the target pixel; $ueq[\cdot]$ represents the number of pixels with gray values different from the target pixel; n is the total number of directions in the k neighborhood of the target pixel; α and β are cost factors, where $\alpha = 0$ if $ueq[f_k(i, j)] = 2$, otherwise $\alpha = 1$; $\beta = 1$ if $eq[f_k(i, j)] = ueq[f_k(i, j)]$, otherwise $\beta = 0$.

After all pixels in Q_S are analyzed via translating M , all identified boundary points within Q_S constitute the structural element T_S . M is translated by one pixel to obtain a new 5×5 sub-region Q_M , and the boundary point determination is repeated until all pixels in Q_S are analyzed. Then, S is translated by one pixel to obtain a new 3×3 sub-region Q_S , and the above procedure is repeated until all pixels are processed. The complete set of obtained structural elements forms the desired adaptive SE. Finally, based on the acquired adaptive structural element, dilation and erosion operations are applied to the water body extraction results.

The dynamic morphological operation enhanced the spatial consistency of the extracted water bodies and mitigated classification errors arising from mixed pixels, emergent vegetation, and variations in SAR backscatter coefficients, thereby improving the overall reliability of the water extraction results. In comparison with conventional morphological approaches based on fixed structural elements, the proposed method exhibits

three notable advantages: (1) maintaining topological consistency in narrow and highly sinuous channels; (2) minimizing shape distortion and information loss during morphological processing; and (3) effectively suppressing noise and filling non-water cavities while preserving fine-scale boundary characteristics.

2.3.4. Accuracy Validation of Water Extraction

This study employs both qualitative and quantitative metrics to evaluate the performance of the water body extraction results. Qualitative assessment is conducted via visual inspection of the extracted water extents. For quantitative evaluation, manually interpreted results serve as the ground truth to construct a confusion matrix. Performance is assessed using several standard metrics, including Precision, Recall, Overall Accuracy (OA), and Average Accuracy (AA). Precision represents the proportion of correctly identified water pixels relative to all pixels classified as water, while Recall indicates the model's ability to detect actual water pixels. Given the inherent trade-off between Precision and Recall, the inclusion of OA and AA ensures a more comprehensive evaluation of extraction efficacy. The corresponding formulas are as follows.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (12)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (13)$$

$$OA = \frac{TP + TN}{TP + FP + FN + TN} \quad (14)$$

$$AA = \frac{1}{2} \left(\frac{TP}{TP + FN} + \frac{TN}{FP + TN} \right) \quad (15)$$

where TP (True Positive) denotes the number of pixels correctly classified as water; FP (False Positive) denotes the number of non-water pixels incorrectly classified as water; FN (False Negative) denotes the number of water pixels incorrectly classified as non-water; and TN (True Negative) denotes the number of pixels correctly classified as non-water.

2.3.5. Spatiotemporal Analysis of Changes During the Flood Season

This study integrates multidimensional datasets to analyze the spatiotemporal evolution of Dongting Lake during the flood season. First, based on the water area extracted from 2015 to 2025, the fluctuation ranges and variation trends were quantified, and inundation frequency was calculated to characterize the spatial stability of water coverage. Second, a regression model was established between in situ water level records and the extracted water area to evaluate the potential for cross-variable estimation. The study further investigated the influence of climatic factors including precipitation, temperature, and sunshine duration on the water area to elucidate their interactive regulatory mechanisms. Finally, the relationship between gauge-measured discharge and water area was analyzed to determine the role of upstream flow in the evolution of the lake's water extent.

3. Results

3.1. Dongting Lake Water Area Extraction

3.1.1. Accuracy Evaluation of Results

To comprehensively evaluate the performance of the proposed water body extraction method, a validation dataset covering different hydrological year types and flood season stages was constructed. The extraction results obtained by the proposed method and four representative methods on the constructed dataset were then cross-validated against man-

ually interpreted reference data. The validation dataset was constructed using a scenario-based stratified sampling strategy. Based on flood-season (April–September) precipitation records from four meteorological stations surrounding Dongting Lake (Yueyang, Hanshou, Yuanjiang, and Xiangyin), the Standardized Precipitation Index (SPI) [38] was calculated to classify the years from 2015 to 2025 into wet, normal, and dry years. Subsequently, five representative years were randomly selected, including one normal year (2021), two wet years (2016 and 2020), and two dry years (2018 and 2023). For each selected year, Sentinel-1 images acquired during the pre-flood, peak-flood, and post-flood periods were chosen, resulting in a total of 15 validation images. For comparison, four widely used water extraction methods were selected, namely the standard Otsu method, GA-Otsu, Support Vector Machine (SVM), and the Sentinel Dual-Polarized Water Index (SDWI). All methods were evaluated using the same performance metrics, including Overall Accuracy (OA), Precision, Recall, and Average Accuracy (AA), to ensure a fair and consistent comparison. The comparison results are presented in Figure 4.

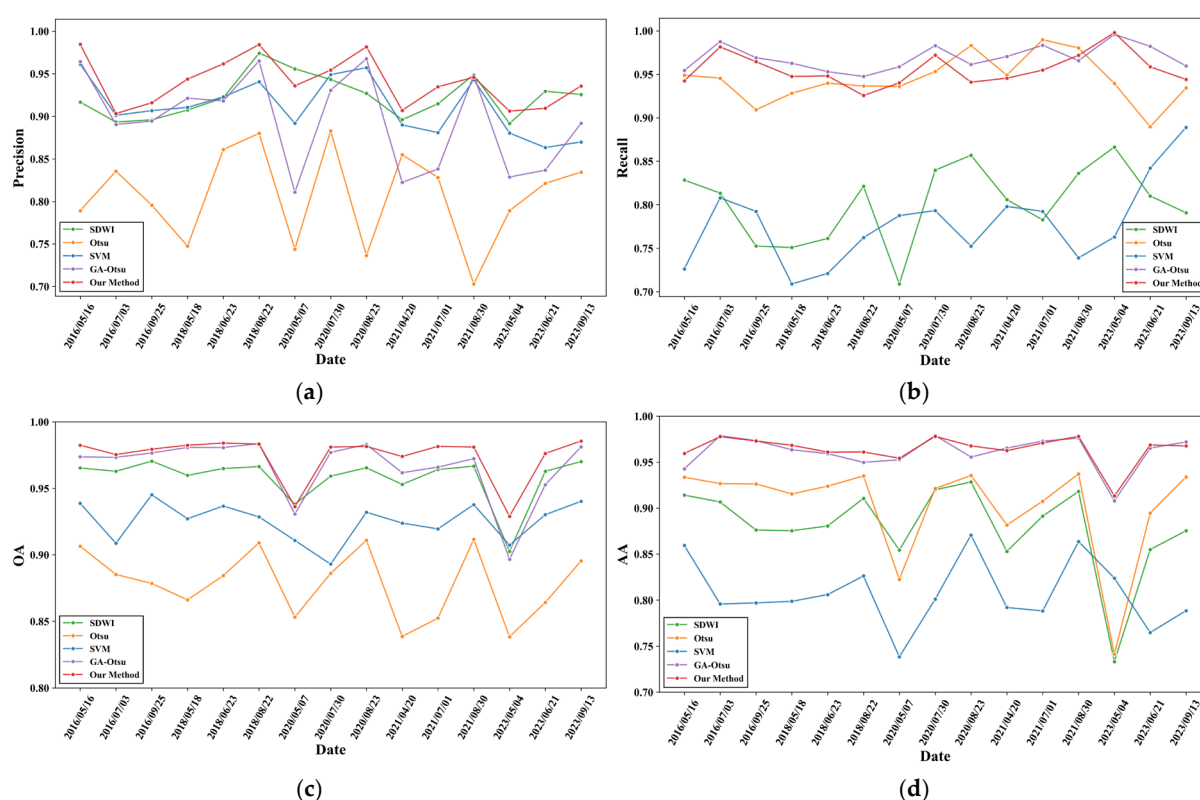


Figure 4. Accuracy comparison of five water extraction methods in Dongting Lake. (a) Precision, (b) Recall, (c) Overall Accuracy (OA), and (d) Average Accuracy (AA).

The experimental results indicate that the proposed method achieved the best overall performance among the five evaluated approaches. The average OA, Precision, and AA reached 0.974, 0.940, and 0.964, respectively, significantly outperforming the standard Otsu, SVM, and SDWI methods, while also slightly exceeding the performance of GA-Otsu. The average Recall was 0.956, which was marginally lower than that of GA-Otsu (0.969). Nevertheless, the proposed method achieved the highest OA, Precision, and AA values for the majority of validation dates and exhibited the smallest performance fluctuations. These findings demonstrate that the proposed method maintains higher extraction accuracy and stronger robustness under different hydrological year types and flood-season stages, thereby further confirming the effectiveness of the proposed framework.

3.1.2. Visualization and Analysis of Results

To reveal the dynamic evolution characteristics of the water extent in Dongting Lake during the flood season, water distribution maps were generated based on the time series from 2015 to 2025, with selected results shown in Figure 5. The results reveal that Dongting Lake typically enters the rising water phase in April–May, followed by a rapid expansion in June–July. The water area reaches its maximum during July–August and subsequently enters the recession period in September. The lake exhibits pronounced seasonal cyclicity, with distinct morphological differences between the rising and receding phases, reflecting a high sensitivity to monsoon precipitation and upstream inflows.



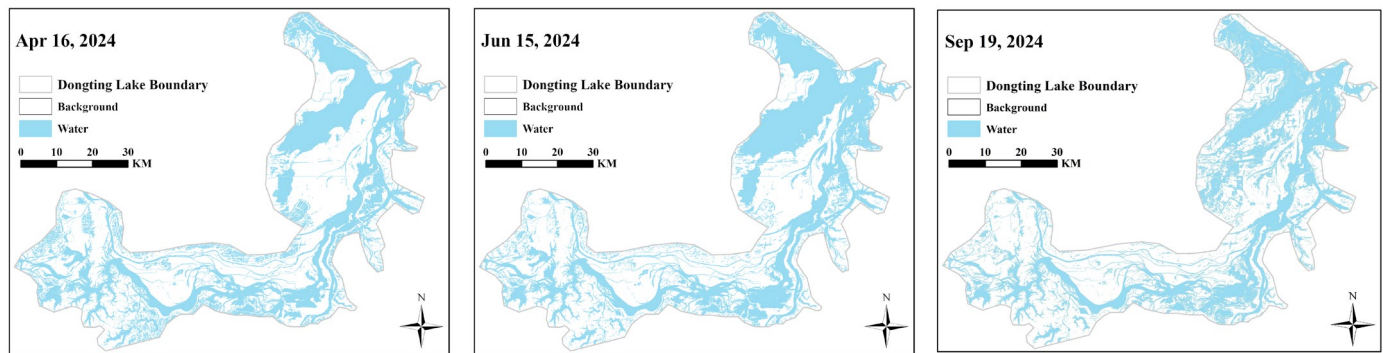


Figure 5. Water Extent of Dongting Lake During the Flood Season.

3.2. Flood-Season Hydrological Dynamics in Dongting Lake

3.2.1. Spatiotemporal Variation in Flood-Season Water Area

During the flood seasons (April–September) from 2015 to 2025, the water area of Dongting Lake exhibited significant interannual fluctuations. As illustrated in Figure 6a, the long-term time series reveals a distinct trend of initial expansion followed by contraction. The maximum water extent reached 2202.26 km² on 30 July 2020, while the minimum was recorded at 614.04 km² on 1 April 2025, with a variance of 1588.22 km². Figure 6b displays the spatial distribution of these extremes. The interannual variation highlights a prominent flood peak in 2020, contrasted by notably lower extents in 2023 and 2025. The 2020 peak is largely attributable to extreme precipitation events across the Yangtze River Basin, whereas the reduced areas in 2023 likely stem from the severe basin-wide drought of 2022. These findings underscore that Dongting Lake’s water extent is subject to high variability closely coupled with extreme climatic events.

The water area of Dongting Lake during the flood season exhibits pronounced intra-annual variability. Based on monthly statistics, Figure 7 presents the maximum, minimum, and mean water areas for each month of the flood season, along with the corresponding years. Overall, the maximum water area gradually increases from 1052.59 km² in April, reaching a peak of 2202.26 km² in July, and declines to 1749.86 km² in September. The minimum water area is only 614.04 km² in April, rises to 885.26 km² in July, and decreases to 762.51 km² in September. The mean water area follows a similar trend, with the lowest value in April (892.56 km²), the highest in July (1538.62 km²), and a reduction to 1066.71 km² in September. During the pre-flood period (April–May), water areas are relatively small but gradually increase, with maximum values rising from 1052 km² to 1550 km² and mean values from 892.56 km² to 1101.71 km², showing a clear upward trend. In the mid-flood period (June–August), the water area reaches its annual peak, with mean values ranging from 1295.78 to 1538.62 km² and July exhibiting the most pronounced increase, as maximum values exceed 2200 km² with substantial fluctuations. During the post-flood period (September), the water area declines markedly, with mean values falling to 1066.71 km², yet remaining higher than the pre-flood period, indicating the transition into the recession phase.

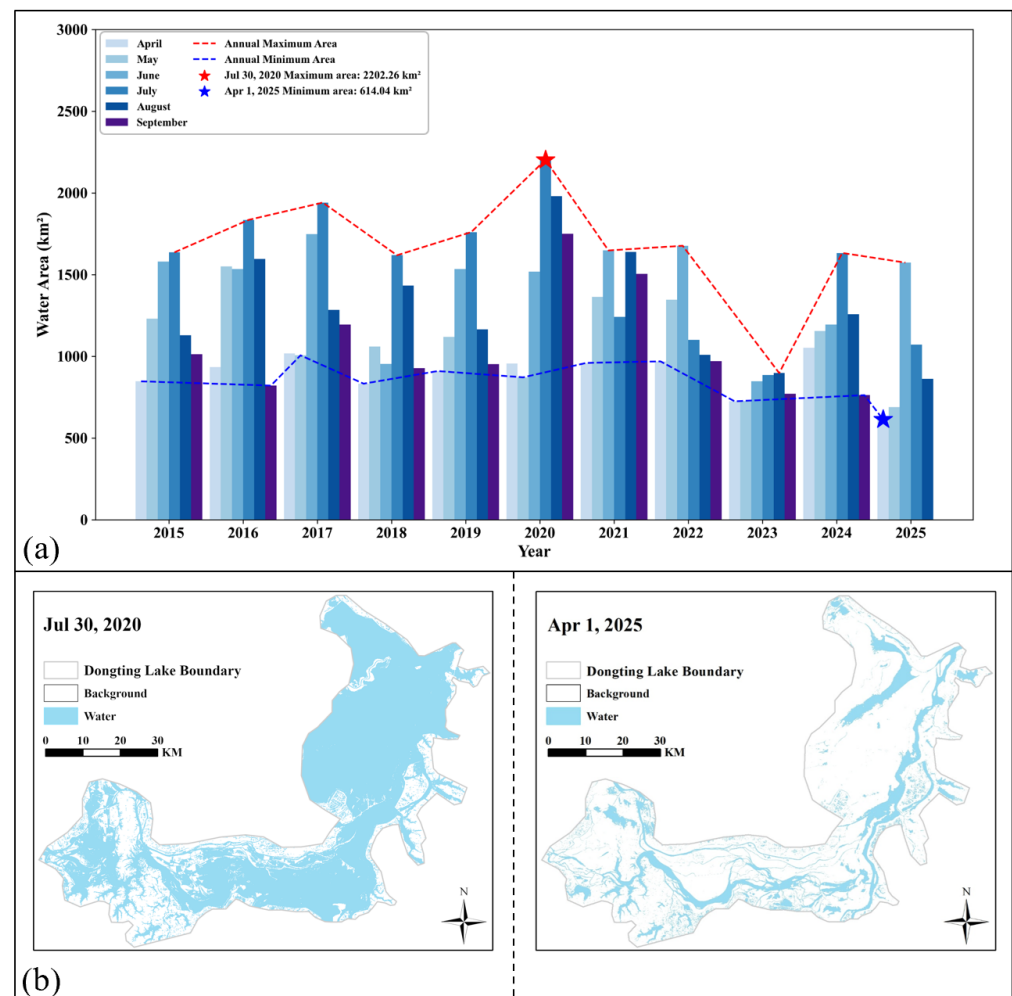


Figure 6. Variations in the flood-season water area of Dongting Lake during 2015–2025. (a) Long-term series of flood-season water area changes during 2015–2025. (b) Maximum and minimum flood-season water extent of Dongting Lake in this study.

The maximum water area and flood-induced expansion trends for 2015–2025 are detailed in Figure 8. Overall, the maximum water area during the flood season exhibited an increasing trend from 2015 to 2020, declined markedly from 2021 to 2023, and showed signs of recovery in 2024–2025. Specifically, from 2015 to 2020, the maximum water area expanded annually, with an average increase of approximately 65.24 km² per year. The flood-season water expansion also steadily increased, indicating that both precipitation and water resource management contributed to an overall increase in lake water extent. Starting in 2021, a turning point occurred in the water area. Between 2020 and 2023, the maximum water area decreased on average by 113.38 km² per year, and the flood-season water expansion declined continuously. Notably, in 2023, extreme drought in the Yangtze River Basin led to a sharp reduction in inflow. Coupled with reservoir impoundment during the low-water period at the Three Gorges Dam, the lake water level dropped significantly, and the water area shrank to extremely low levels. From 2024 onward, improved interannual precipitation and enhanced water regulation measures contributed to better water storage conditions, resulting in localized recovery and expansion of the flood-season water area.

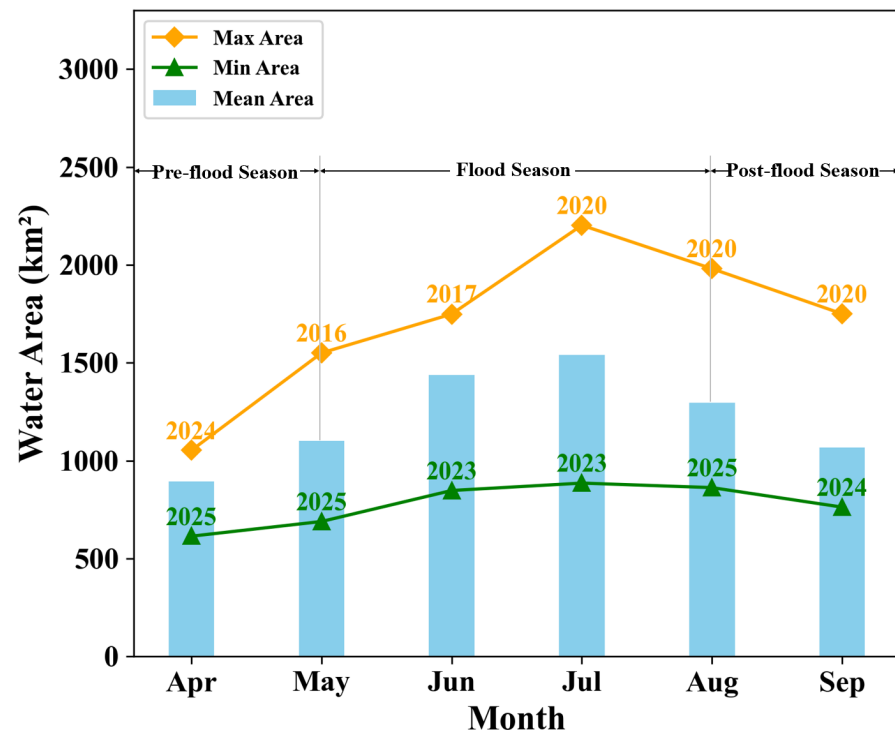


Figure 7. Monthly maximum, minimum, and average water area of Dongting Lake during the flood season from 2015 to 2025 (the numbers on the lines indicate the corresponding years).

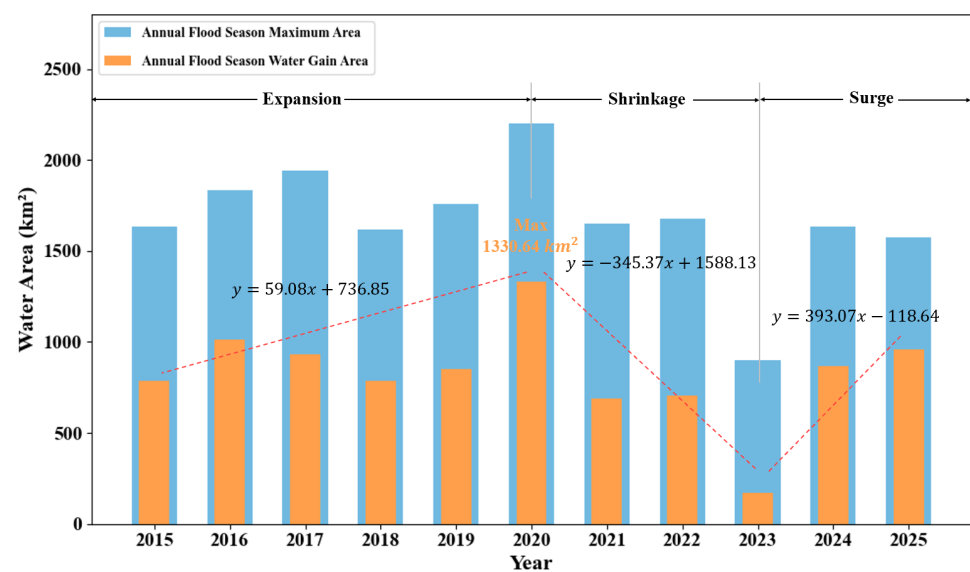


Figure 8. Maximum Water Surface Area and Expansion Trend of Dongting Lake During Flood Seasons from 2015 to 2025.

3.2.2. Analysis of Flood-Season Inundation Frequency

To further elucidate the spatiotemporal characteristics of water coverage in Dongting Lake during the flood seasons of 2015–2025, this study superimposed 65 temporal extraction results to calculate regional inundation frequencies, as illustrated in Figure 9.

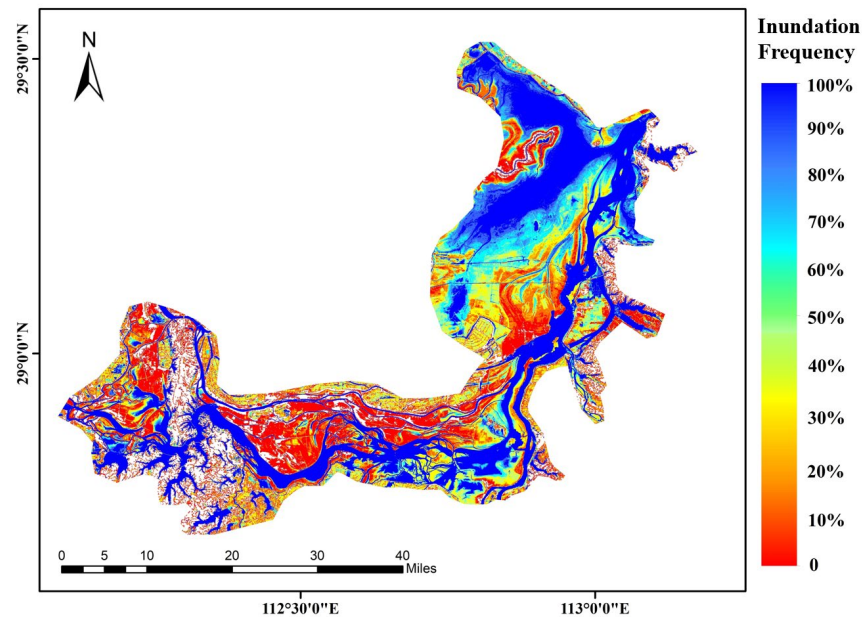


Figure 9. The Inundation Frequency Distribution Map of Dongting Lake during the Flood Seasons from 2015 to 2025.

The spatial distribution exhibits a distinct pattern of “deeper in the north and shallower in the south, with higher elevation in the central lake bed compared to the periphery,” reflecting pronounced hydrological heterogeneity. Based on inundation frequency, the surface water is classified into permanent and temporary water bodies. Permanent water bodies, characterized by year-round persistence and minimal seasonal variation, are primarily concentrated in the central and northern regions, exhibiting inundation frequencies exceeding 90% (represented in dark blue). In contrast, temporary water bodies are seasonal and predominantly distributed across the southwestern and eastern floodplains. These areas consist of wetlands or agricultural lands during the dry season that become periodically submerged during the flood season due to upstream inflows and intense precipitation. Overall analysis indicates that flood risk within the Dongting Lake basin is generally high, particularly in the low-lying plains and light-blue zones, which represent high-vulnerability regions. Medium-frequency zones also exhibit elevated risk under extreme climatic conditions. To mitigate these threats, it is imperative to strengthen embankment and hydraulic infrastructure, optimize flood diversion and drainage systems, and integrate remote sensing with hydrological modeling to enhance forecasting and regulation capacities. Furthermore, reinforcing wetland conservation and lake restoration initiatives, such as the “returning farmland to lake” program, is essential for restoring the lake’s natural flood-storage and regulatory functions.

3.2.3. Analysis of the Relationship Between Water Level and Area

The relationship between water area and water level is a fundamental indicator of the hydrological dynamics in lake systems, and its accurate characterization is essential for ecological conservation and disaster mitigation. In this study, the water area of East Dongting Lake during the 2015–2025 flood seasons was extracted and correlated with in situ water level observations from the Chenglingji gauge station, as illustrated in Figure 10. Statistical analysis reveals an average flood-season water level of approximately 26.88 m, corresponding to a mean water area of 1224.46 km². The peak water level of 34.47 m occurred on 30 July 2020, with a maximum area of 2202.26 km², while the minimum level was recorded on 18 September 2022, at 20.22 m, corresponding to an area of 970.79 km². Regression analysis yielded a coefficient of determination (R^2) of 0.9312, demonstrating a

robust positive correlation. These results suggest that remote sensing-derived water area is a reliable proxy for predicting water level variations, providing critical scientific support for flood risk assessment.

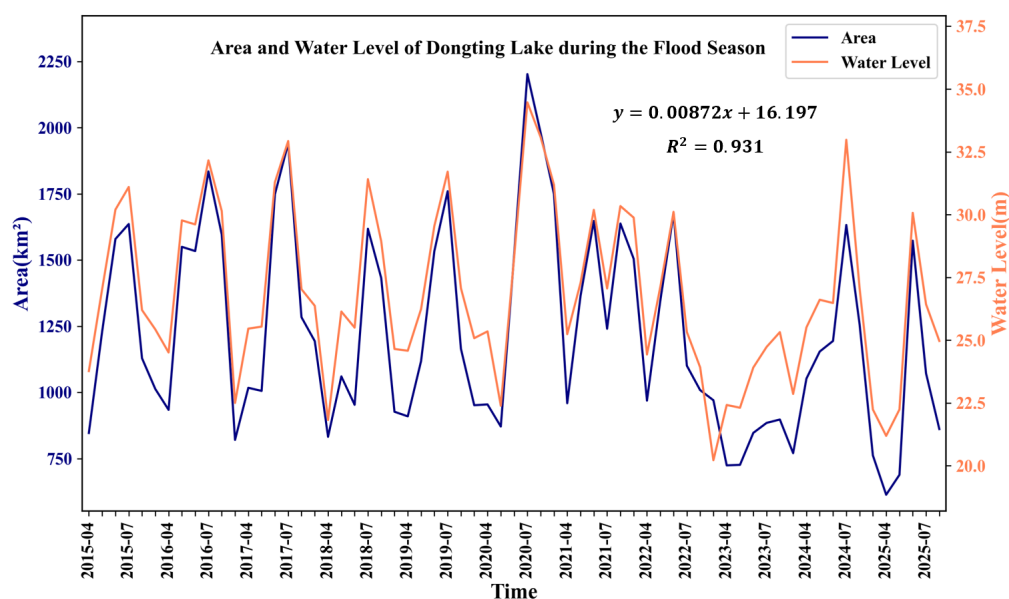


Figure 10. Variation Curves of Water Area and Water Level during the Flood Season in Dongting Lake.

4. Discussion

4.1. Impact of Climatic Factors

Changes in the natural environment exert significant impacts on lake ecosystems. To quantitatively investigate the effects of meteorological factors and antecedent hydrological conditions on monthly water-area variations in Dongting Lake, the monthly water-area change was selected as the dependent variable, while precipitation, mean air temperature, sunshine duration, and antecedent water area were considered as candidate explanatory variables. Considering that lake-area responses to meteorological forcing may exhibit nonlinear characteristics and that the available dataset was relatively limited (43 samples), first-, second-, and third-order polynomial terms were generated for each variable, resulting in a total of 12 candidate predictors, as defined in Equation (16).

$$X = [P, P^2, P^3, T, T^2, T^3, S, S^2, S^3, A_0, A_0^2, A_0^3] \quad (16)$$

where P is the cumulative precipitation during the study period (mm); T is the mean temperature during the study period ($^{\circ}\text{C}$); S is the cumulative sunshine duration during the study period (h); A_0 is the initial water storage at the beginning of the month (km^2).

Because strong multicollinearity may exist among higher-order polynomial terms, direct regression using all variables could lead to unstable parameter estimates and an increased risk of overfitting. Therefore, the Least Absolute Shrinkage and Selection Operator (LASSO) [39] was employed for variable selection. By introducing an L1 regularization term into the ordinary least squares objective function, LASSO shrinks regression coefficients and forces less important variables toward zero. The objective function O is given in Equation (17). A 10-fold cross-validation procedure was applied to determine the optimal regularization parameter (λ) and identify the most parsimonious predictor set.

$$O = \min \left\{ \sum_{i=1}^n (y_i - \hat{y}_i)^2 + \lambda \sum_{j=1}^p |\beta_j| \right\} \quad (17)$$

where y_i is the observed value; $\hat{y}_i$ is the predicted value; β_j is the regression coefficient; p is the number of candidate variables; λ is the regularization parameter.

The LASSO results indicated that only precipitation (P), the cubic term of temperature (T^3), sunshine duration (S), the cubic term of sunshine duration (S^3), and antecedent water area (A_0) were retained in the final model, whereas the coefficients of all remaining variables were reduced to zero. Ordinary least squares regression was subsequently performed using the selected predictors, yielding the optimal multiple regression model (as shown in Equation (18)). The model achieved a coefficient of determination R^2 of 0.673, a root mean square error ($RMSE$) of 234.9 km², and a mean absolute error (MAE) of 194.3 km², indicating that approximately 67% of the monthly variability in water-area change could be explained by the selected variables.

$$\Delta A = 1.839P - 0.0023T^3 - 1.551S - 8.72 \times 10^{-7}S^3 - 0.481A_0 + 683.99 \quad (18)$$

where ΔA is the monthly change in water area (km²).

Among the retained predictors, precipitation was identified as the primary positive driving factor, with a regression coefficient of 1.839. Holding other variables constant, a 100 mm increase in precipitation corresponded to an average increase of approximately 183.9 km² in water area. This indicates that flood-season precipitation promotes lake expansion through direct rainfall and watershed runoff inputs. Notably, neither the quadratic nor cubic precipitation terms were retained in the final model, suggesting an approximately linear precipitation–water area relationship within the observed range. The coefficient of antecedent water area was −0.481, indicating that larger initial lake extents were associated with smaller subsequent increases in water area. Specifically, every 100 km² increase in antecedent water area resulted in an average reduction of 48.1 km² in subsequent water area variation. This reflects a clear antecedent-state dependence, whereby the initial storage condition constrains the lake’s expansion potential.

Nevertheless, flood-season water area dynamics in Dongting Lake are also influenced by other hydrological factors, particularly the operation of the Three Gorges Reservoir and river–lake interactions. Reservoir impoundment during September–October reduces downstream discharge and lowers the water level at Chenglingji, accelerating lake recession, whereas dry-season water releases may help maintain lake levels. In addition, flow diversion, sediment transport, and channel adjustment processes between the Jingjiang River and Dongting Lake directly affect flood inflows and the lake’s storage capacity. These factors may strengthen or offset precipitation effects, leading to interannual variability in the precipitation–water area relationship.

Temperature and sunshine duration mainly affect water area dynamics through evapotranspiration. Temperature entered the final model only through a negative cubic term, indicating a nonlinear increase in water loss under high-temperature conditions. Sunshine duration included both linear and cubic terms, both with negative coefficients, suggesting that longer sunshine duration enhances evaporation and reduces water area, with the effect becoming stronger under prolonged sunshine conditions.

The relationships between monthly mean water area variation and three meteorological factors, namely precipitation, mean air temperature, and sunshine duration, were further investigated. The results of the correlation analysis and linear regression are presented in Figure 11. The figure provides the sample size, Pearson correlation coefficients, significance levels (p -values), and the corresponding regression equations.

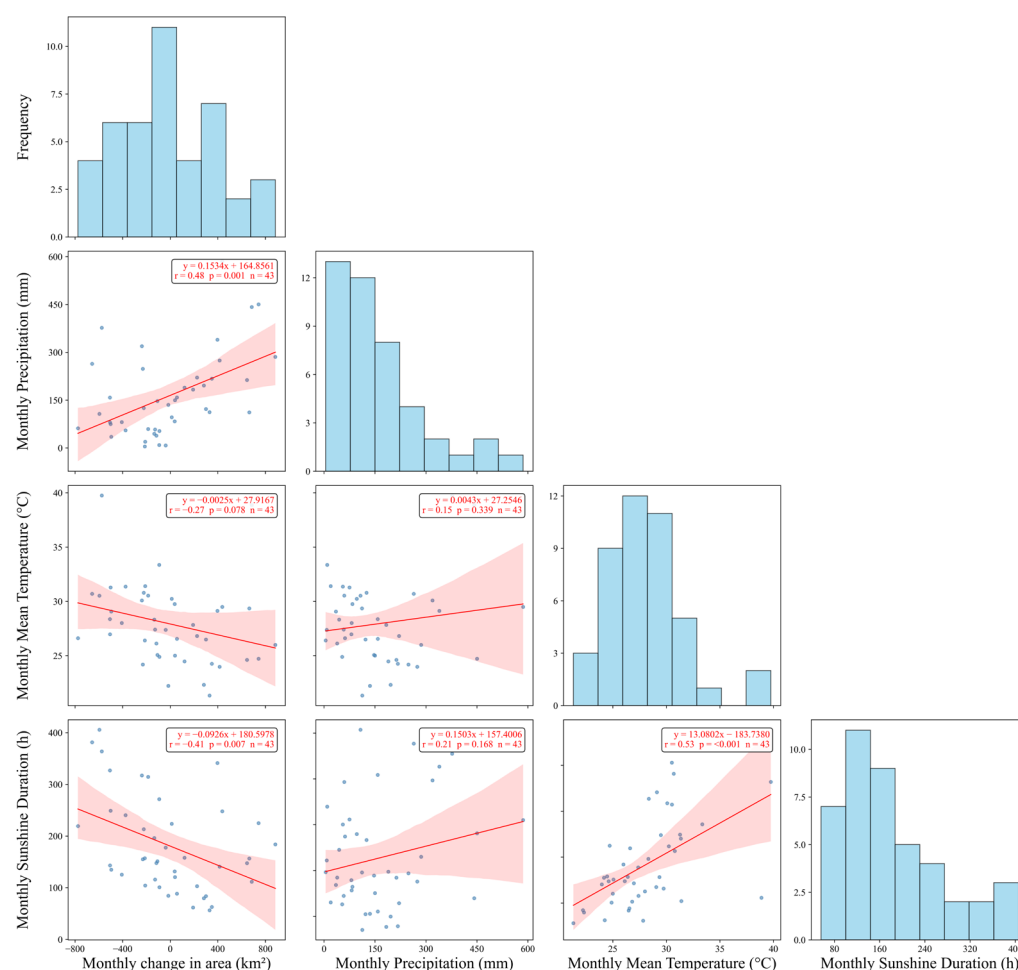


Figure 11. Correlation Analysis of Dongting Lake Water Area and Climatic Factors During the Flood Season.

The results indicate that monthly mean water area variation is significantly and positively correlated with monthly precipitation, with a Pearson correlation coefficient of 0.48, suggesting that precipitation is an important driver of water area expansion. In contrast, monthly mean water area variation exhibits a significant negative correlation with monthly sunshine duration (r is -0.41), indicating that longer sunshine duration may suppress water area growth by enhancing evapotranspiration. A weak negative correlation was observed between monthly mean air temperature and monthly mean water area variation (r is -0.27); however, this relationship did not reach statistical significance. In addition, monthly mean air temperature showed a significant positive correlation with monthly sunshine duration (r is 0.53), reflecting the intrinsic linkage between thermal conditions and solar radiation in the study area.

Overall, monthly water-area variations in Dongting Lake were jointly controlled by precipitation inputs, antecedent storage conditions, and evaporative losses. Precipitation served as the dominant driver of lake expansion, antecedent water area reflected the hydrological memory effect of the lake system, and temperature and sunshine duration contributed to lake contraction through evapotranspiration processes. It should be noted that only local meteorological variables and antecedent water area were considered in the present analysis. Important hydrological drivers, such as inflows from the Yangtze River, runoff from the four tributary river systems, and hydraulic regulation associated with large-scale water-control projects, were not included. Consequently, part of the unexplained variance may be attributed to these external hydrological influences.

4.2. Impact of Flow Rate Factor

The relationship between discharge and the water area of Dongting Lake is fundamental to understanding flood-season hydrodynamics and informing flood control operations in the middle and lower reaches of the Yangtze River. Utilizing water area estimates and observed discharge from the Chenglingji gauge station, this study established the statistical relationship between these variables during the 2015–2025 flood seasons (April–September), as illustrated in Figure 12. The results show a significant positive correlation, with a coefficient of determination $R^2=0.802$, indicating that flow rate is a key factor influencing the water area. However, unlike the relatively stable timing of lake water volume and precipitation peaks, the timing of peak river discharge into the Yangtze varied considerably across years. Peak discharge occurred in July for 2015, 2016, 2017, 2019, 2020, and 2024; advanced to June in 2021, 2022, and 2025; and arrived exceptionally early in April 2023. Representative cases illustrate this variability. On 12 July 2019, flow rate reached 28,200 m^3/s due to concentrated rainfall and strong water release. On 23 August 2020, discharge was only 12,500 m^3/s , influenced by impoundment at the Three Gorges Reservoir and high-water backflow effects. On 30 July 2024, flow rate reached 25,200 m^3/s under the combined effects of heavy rainfall and operational regulation. In contrast, low-flow years were concentrated in 2022 and 2023, when reduced precipitation and elevated mainstream water levels led to generally lower flow rate.

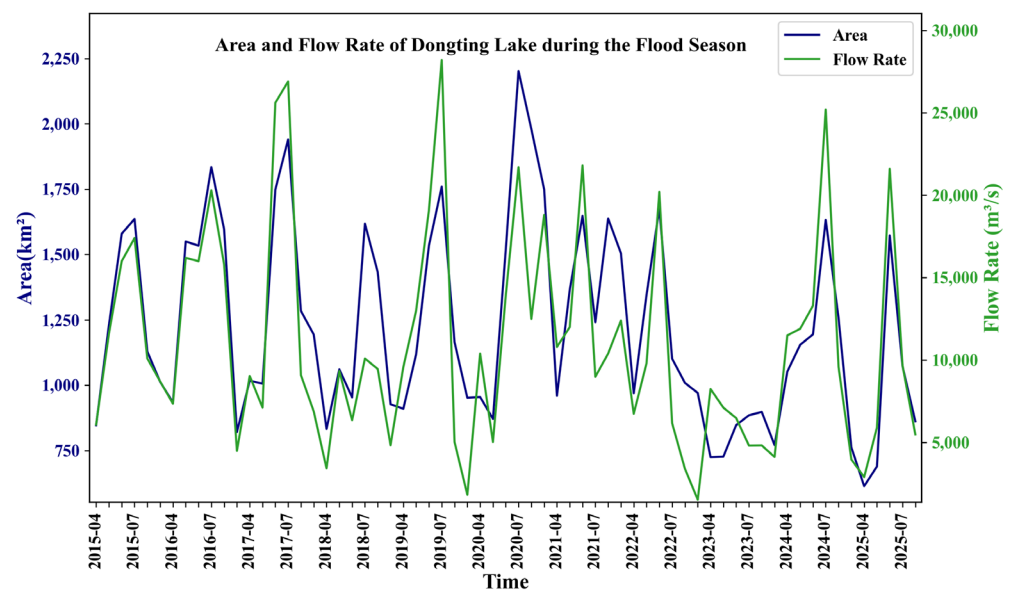


Figure 12. Correlation Analysis of Dongting Lake Water Area and Flood Rate Factors.

In summary, while water area is strongly correlated with discharge, their relationship is substantially modulated by external factors, including Yangtze River mainstream water levels, Three Gorges Reservoir operations, and anthropogenic interventions. Consequently, hydrological forecasting for Dongting Lake must comprehensively account for backwater effects, joint reservoir regulation, and levee safety to enhance predictive accuracy and improve regional risk management capacity.

5. Conclusions

This study focuses on Dongting Lake, the second-largest freshwater lake in China, and leverages Sentinel-1 polarimetric SAR data integrated with the Google Earth Engine platform to extract a long-term time series of flood-season water surface areas from 2015 to 2025. By synthesizing multi-source datasets, including precipitation, discharge, tem-

perature, and water level, we systematically analyzed the lake's hydrological characteristics and their underlying driving mechanisms. The primary conclusions are as follows:

- (1) A robust water extraction framework for Sentinel-1 polarimetric SAR imagery was developed by integrating the SDWI, Otsu maximum between-class variance thresholding, and a genetic algorithm, followed by dynamic morphological refinement. The proposed method effectively reduces interference from mudflats and emergent vegetation, resulting in improved water delineation accuracy under the complex hydrological conditions of the flood season.
- (2) During the 2015–2025 flood seasons, the water surface area of Dongting Lake exhibited substantial interannual variability, showing an overall pattern of increase followed by decline. The maximum extent (2202.26 km²) was recorded on 30 July 2020, whereas the minimum extent (614.04 km²) occurred on 1 April 2025, with an average area of 1228.97 km². Extreme precipitation contributed to the 2020 expansion, while persistent drought conditions were primarily responsible for the reduced extents observed in 2023 and 2025.
- (3) Inundation frequency analysis revealed a distinct spatial pattern characterized by higher frequencies in the north and central regions and lower frequencies in the south and peripheral zones. Permanent water bodies were mainly distributed in the central and northern lake areas, whereas the southwestern and eastern mudflats functioned as seasonal water bodies. Areas with high flood susceptibility were concentrated in low-lying plains, underscoring the importance of embankment reinforcement, drainage optimization, and wetland restoration for flood mitigation.
- (4) Water surface area exhibited a very strong positive relationship with water level, with the regression model yielding an R^2 value of 0.9312. This result indicates that variations in water extent can reliably reflect fluctuations in lake water level and highlights the potential of remotely sensed water area as an effective indicator for hydrological monitoring and flood forecasting.
- (5) Among the examined climatic variables, precipitation was identified as the dominant factor controlling water surface area dynamics, with extreme rainfall events inducing rapid lake expansion. In contrast, temperature and solar radiation mainly influenced hydrological processes through evapotranspiration and played comparatively minor roles during periods of intense precipitation. These findings suggest that water body evolution is governed by the combined effects of multiple climatic drivers rather than any single factor.
- (6) Flow rate showed a significant positive correlation with water surface area ($R^2 = 0.802$), indicating its important role in regulating lake inundation dynamics. However, the timing and magnitude of peak discharge were strongly influenced by external controls, including Yangtze River water levels, Three Gorges Reservoir operations, and human engineering activities. Therefore, effective flood management should incorporate hydrological connectivity, reservoir regulation, and extreme climate variability to enhance forecasting reliability and risk mitigation.

Despite these insights, certain challenges remain. First, metallic reflections (e.g., from ship rooftops) produce radar artifacts that may bias area estimates; future research should incorporate ship detection and masking. Second, while the “Four Rivers” (Xiang, Zi, Yuan, and Li) are critical contributors, data constraints limited their full integration; future studies should employ comprehensive hydrological modeling for a complete water balance. Finally, the long-term impact of human activities, such as land-use change and hydraulic engineering, requires further quantitative assessment through diverse mathematical modeling to support sustainable basin management and ecological conservation.

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