

Article

Remote Sensing Dynamic Monitoring and Driving Mechanism of Lake Area in Ebinur Lake, 1992–2024

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Abstract

Arid inland saline lakes are key components of basin ecosystems. As the largest saline lake in Xinjiang and a critical ecological barrier in northwest China, Ebinur Lake's area dynamics are vital to regional sustainable development. This study integrates Landsat imagery (1992–2024) with meteorological and socio-economic data to investigate optimal water extraction methods, spatio-temporal lake area variations, and driving mechanisms. Multiple methods were employed, including water index comparison, Mann–Kendall test, Pearson correlation, and ridge regression. Results show that: (1) the Normalized Difference Water Index (NDWI) maintains high, stable classification accuracy across years and months, making it suitable for long-term monitoring; (2) from 1992 to 2024, lake area demonstrates a significant fluctuating downward trend without abrupt change points, indicating continuous degradation. During the growing season (April–October), it first decreases and then increases, with larger early-season areas, minima in August and September, coinciding with peak agricultural irrigation demand; (3) regarding driving mechanisms, socio-economic factors dominate (approximately 70%), while meteorological factors play a weakly regulatory role (about 30%). Population growth and increased water consumption are the primary drivers, with obvious seasonal differences. Meteorological changes, socio-economic development, and ecological measures jointly influence lake area. Although extreme events (e.g., anomalous precipitation) induce short-term fluctuations, they do not alter the long-term degradation trend dominated by human activities. This study provides methodological support for long-term monitoring of arid saline lakes and scientific evidence for ecological conservation and water resource management in the Ebinur Lake Basin.

Keywords: Ebinur Lake; water extraction; lake area dynamics; driving mechanism; saline lake; arid region

Academic Editor: Ting On Chan

Received: 12 June 2026

Revised: 18 July 2026

Accepted: 24 July 2026

Published: 25 July 2026

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1. Introduction

Arid inland saline lakes are terminal sinks of basin-scale water circulation, with irreplaceable functions in maintaining regional ecological balance and biodiversity [1–3]. As an important component of arid zone surface water systems, lake area fluctuations directly reflect changes in basin water resources and eco-environmental conditions, closely linked to wetland evolution, biodiversity maintenance, and aeolian processes [4–6]. Due to their limited water supply, high salinity, and strong evaporation, saline lakes in arid regions are highly sensitive to external disturbances [7–9]. With sustained climate change and human activities, many arid-region saline-alkaline lakes worldwide (e.g., the Caspian Sea, the Aral Sea) are shrinking rapidly, causing habitat loss and severe ecological degradation that threaten water resources, environmental security, and human health [10,11]. In arid northwest China, similar challenges are prominent, with many inland terminal lakes undergoing varying degrees of water loss and ecological degradation [12–14]. Among them, Ebinur Lake typifies inland saline lake faces simultaneous water depletion and ecological deterioration [15].

Ebinur Lake is a core ecological security barrier in the western Junggar Basin, and its area dynamics directly affect basin ecosystem stability [16]. In recent decades, driven jointly by climate change and intensive human activities, Ebinur Lake has experienced pronounced area fluctuations and overall shrinkage. This causes eco-environmental problems, including lakeshore wetland degradation, intensified salt-dust hazards, and expanded soil salinization, constraining regional socio-economic sustainability [17]. With its special geographical location, closed basin structure, and critical regulatory role in regional ecosystems, Ebinur Lake has long attracted extensive attention [18,19]. Previous studies on lake area variation, ecological degradation processes, and environmental effects have consistently shown that, since the late 20th century, Ebinur Lake's area has exhibited an overall fluctuating downward trend with distinct phased characteristics [13,20].

For lake area monitoring, remote sensing has become an essential technical support for dynamic monitoring of Ebinur Lake, owing to its advantages of large-scale coverage, long-term and multi-scale observation [21,22]. Current studies have utilized multi-source remote sensing data (e.g., Landsat, Sentinel) and applied various approaches including water indices and object-oriented classification methods to investigate Ebinur Lake's surface changes [23,24]. However, due to research objectives and data availability, differences among previous studies in data sources, study periods, and water extraction methods [13,25]. Existing studies either focus on short-term periods or rely on annual or single-month representations, limiting characterization of long-term and intra-annual lake dynamics [25–27]. Additionally, Ebinur Lake features high salinity, widespread saline crusts and bare land along the lakeshore, and frequent salt-dust disturbances. Methodological differences in boundary identification and fragmented water detection lead to inconsistent lake area results across studies [20,26]. This heterogeneity based on data hampers direct comparison and integration of results, hindering a coherent understanding of Ebinur Lake's long-term evolution [28].

In driving mechanisms, existing studies mainly attribute Ebinur Lake area change to meteorological (e.g., precipitation, temperature) and socio-economic factors. Most studies, conducted primarily at the annual scale, consistently conclude that human activities dominate lake degradation [13,29]. However, socio-economic drivers are often characterized using indirect indicators, such as population size or Gross Domestic Product (GDP), while insufficient attention has been given to water consumption, which directly reflects basin water use intensity [30]. For closed-basin terminal lakes such as Ebinur Lake, increases in agricultural, industrial, and domestic water use directly reduce lake inflow, making water consumption a more explicit indicator of human influence on lake hydrological processes. Moreover, most analyses remain limited to qualitative descriptions or correlation level,

lacking systematic quantification of different driving factors' relative contributions and seasonal differentiation of driving mechanisms [20,30,31]. For instance, the study tracked monthly lake changes but did not quantitatively incorporate basin water consumption, seasonal driver variations, or the relative contribution of each driving factor [20].

Collectively, existing studies on Ebinur Lake are hampered by two core knowledge gaps: the absence of consistent monthly long-term lake area datasets supported by systematic water index evaluation under salt crust spectral interference, and the lack of quantitative decomposition of meteorological and socio-economic driving contributions. Based on the above limitations, this study integrates Landsat imagery (1992–2024) with meteorological and socio-economic data to systematically examine lake area dynamics and driving mechanisms. Specifically, this study aims to: (1) compare and evaluate the extraction accuracy of common water indices (NDWI, MNDWI, AWEI, MAWEI), under the high-salinity and strong-interference conditions of Ebinur Lake, identifying the optimal method; (2) analyze lake area variation characteristics and fluctuation patterns across growing season stages (interannual: May and August; intra-annual: April–October), clarifying phased evolution differences; (3) quantitatively assess the relative contributions of meteorological factors (temperature, precipitation, wind speed) and socio-economic factors (population, GDP, water consumption) to lake area change, unraveling monthly variations in driving mechanisms. This study provides methodological reference for long-term, high-precision monitoring of arid-region saline lakes and offers scientific support for ecological conservation and water resource allocation in the Ebinur Lake Basin.

2. Materials and Methods

2.1. Study Area

Ebinur Lake (44°45′–45°09′ N, 82°35′–83°11′ E) lies in the northern Tianshan piedmont, Xinjiang, at the southwestern Junggar Basin margin (Figure 1). Administratively, it is situated in northwestern Xinjiang Uygur Autonomous Region, with the Alashankou Pass to the northwest connecting directly to Kazakhstan, forming an important corridor between China and Central Asia. It is Xinjiang's largest saline lake and terminal lake of the Kuitun, Jing and Bortala Rivers. The lake is adjacent to the Alashankou wind corridor with prevailing northwest winds; it experiences 164 annual Force 8 strong wind days (max 55 m·s⁻¹) [32]. Average annual precipitation over the lake is approximately 90.9 mm, while annual evaporation reaches about 1662 mm [11,33], resulting in high salinity (85–124 g·L⁻¹). Currently, the primary inflow rivers are the Bortala River and the Jing River.

The Ebinur Lake Basin covers approximately 50,375 km² and is a typical arid-region mountain–oasis–desert–lake coupled ecosystem, featuring ecological fragility and significant ecological function [34]. Over recent decades, land and water resource development has reduced inflow, shrinking the lake area to 542 km² by the late 20th century [35,36]. Continued lake shrinkage has caused lakebed exposure, vegetation degradation, and accelerated desertification. Combined with frequent strong winds, sand and salt-dust storms in the region are prevalent, exacerbating ecological problems [37].

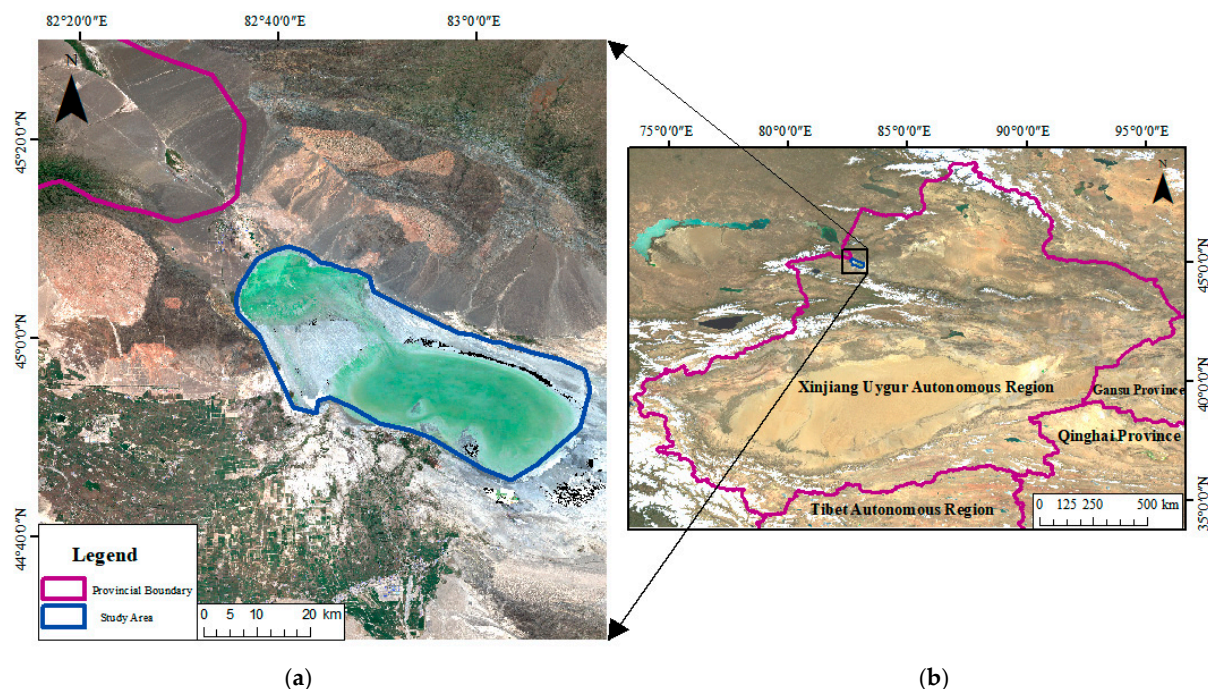


Figure 1. Location of study area: (a) remote sensing map of the Ebinur Lake study area; (b) regional overview map showing the position of Ebinur Lake within Xinjiang Uygur Autonomous Region and adjacent provinces.

2.2. Data Sources and Processing

- (1) Remote sensing data. Sourced from Landsat satellite missions (5 TM, 7 ETM+, 8 OLI/TIRS, 9 OLI2/TIRS-2) (Table 1) and obtained through the Google Earth Engine (GEE) platform (<https://earthengine.google.org/>) [38].
- (2) Meteorological data. Obtained from the Jinghe meteorological station, the closest to the lake area. The dataset includes monthly average temperature, cumulative monthly precipitation (20:00–20:00), and monthly maximum 10 min average wind speed (hereafter referred to as wind speed) for May and August, 2004–2021, from the China Meteorological Data Service Centre (<http://data.cma.cn/>).
- (3) Socio-economic data. Primarily include population, GDP, and water consumption, from the *Xinjiang Statistical Yearbook* (2004–2022). 2012 GDP data is supplemented from the *Statistical Communique of Bortala Mongolian Autonomous Prefecture on the 2024 National Economic and Social Development*.

Landsat imagery preprocessing:

- (1) All Landsat imagery used in this study is USGS Collection 2 Tier 1 Level-2 surface reflectance products, provided by the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (Sioux Falls, SD, USA), which have undergone official atmospheric correction and radiometric scaling conversion to unify the surface reflectance range across 8-bit Landsat 5/7 and 12/14-bit Landsat 8/9 sensors and eliminate primary inter-sensor radiometric bias. Cloud and cloud shadow pixels were masked using QA_PIXEL quality bands; focal mean gap-filling was additionally applied to Landsat 7 ETM+ scenes with SLC-off scan-line gaps. Residual sensor-specific spectral discrepancies and salt-crust interference were further addressed via the image-wise histogram-assisted thresholding strategy described in Step (3), thereby ensuring long-term series comparability of lake area results.
- (2) Calculating water indices from specific spectral bands.

- (3) Converting water index images to binary water masks via a semi-automated thresholding workflow. Specifically, for each monthly composite NDWI image, the pixel histogram was first analyzed to distinguish two distinct pixel modes corresponding to open water and salt-crust-covered backgrounds, and the valley position between the two modes was extracted as the preliminary segmentation threshold. This initial threshold was then refined through visual interpretation against contemporaneous high-resolution Google Earth imagery and fine-tuned to achieve the best visual agreement with the actual shoreline. This image-by-image calibration strategy mitigates spectral variations induced by salt crust interference and cross-sensor radiometric discrepancies. Finally, morphological opening and closing operations with a 3×3 pixel circular kernel were applied to the binary classification results to remove scattered noise pixels and fill small internal gaps within water bodies.
- (4) Calculating and visualizing lake area from validated extraction results. For monthly composites suffering from persistent cloud contamination or complete data absence, a tiered seasonal substitution strategy confined strictly to the April–October growing season was implemented to reconstruct valid NDWI baselines for target May and August scenes: First, cloud-free images from the preceding or subsequent months within the same year were used as the primary substitute. When both adjacent months had valid data, their average was adopted; if only one was available, that single scene was used to minimize short-term water level fluctuations. Second, if no qualified intra-year imagery existed, the NDWI average of same-month cloud-free composites from the closest adjacent years served as the secondary alternative. In addition, for small water patches that could not be reliably extracted via GEE due to shadow or extreme salt-crust spectral interference, supplementary manual area calibration was conducted in ArcGIS 10.8 to complement the dataset.

Table 1. Data sources.

Sensor	Year	Months Used in This Study	Spatial Resolution	Calling Code in GEE
Landsat5 TM	1992–1993, 1995–1998, 2007, 2011	May, August		'LANDSAT/LT05/C02/T1_L2'
	1994	May, June, August		
	2010	April–October		
	1999–2003, 2005, 2008, 2012	May, August		
Landsat7 ETM+	2004	May, June, August	30 m	'LANDSAT/LE07/C02/T1_L2'
	2006, 2009	April–October		
	2013, 2017–2021, 2023	May, August		
Landsat8 (OLI/TIRS)	2014	May, June, August		'LANDSAT/LC08/C02/T1_L2'
	2015, 2016, 2024	April–October		
Landsat9 (OLI2/TIRS-2)	2022	May, August		'LANDSAT/LC09/C02/T1_L2'

Notably, considering image quality and waterbody morphology stability, June of 1994, 2004, 2014, and April–October of 2024 were selected as representative accuracy assessment samples to ensure water body extraction model stability and results accuracy. Furthermore, as available Landsat imagery for May and August covers 1992–2024 in full, they were selected to characterize seasonal and interannual lake area variations. In driving mechanism analysis, socio-economic statistical data were only available for 2004–2021, so lake area data from the same period were used for analyses.

2.3. Research Methods

2.3.1. Water Indices

Four water indices (NDWI, MNDWI, AWEI, and MAWEI) were selected to extract surface water bodies from Landsat imagery (Table 2).

Table 2. Summary of water indices used in this study.

Water Index	Formula	Characteristics	References
Normalized Difference Water Index (NDWI)	$NDWI = \frac{Green - NIR}{Green + NIR}$	Effective for open water body extraction; susceptible to interference from high-reflectance non-water backgrounds such as buildings.	[39]
Modified Normalized Difference Water Index (MNDWI)	$MNDWI = \frac{Green - SWIR1}{Green + SWIR1}$	Replacing the Near Infrared (NIR) band with the Short Wave Infrared (SWIR) band, which helps suppress built-up noise and improves water extraction in urban environments.	[40,41]
Automated Water Extraction Index (AWEI)	$AWEI_{sh} = \frac{Blue + 2.5Green - 1.5(NIR + SWIR1) - 0.25SWIR2}{(NIR + SWIR1) - 0.25SWIR2}$	Effectively distinguishes water bodies from shadows or complex backgrounds, with two scenarios: AWEI _{nsh} and AWEI _{sh} . This study employs the AWEI _{sh} , which incorporates the blue band to address scenarios where shadows dominate the interference information.	[42]
Modified Automatic Water Extraction Index (MAWEI)	$MAWEI = 5(Green - NIR) + (Blue + Red - 4SWIR2)$	Rapidly extracting large-area water bodies and applying them in regional mapping and land use classification, with the ability to distinguish bright urban features.	[43]

2.3.2. Accuracy Assessment

To assess the accuracy of the water extraction results, 82 reference points were randomly generated using ArcGIS across the entire Ebinur Lake study area, ensuring spatial coverage of both water and non-water surfaces. All candidate points underwent strict screening by cross-referencing cloud-free Landsat composites and contemporaneous high-resolution Google Earth imagery. The water/non-water class of each retained point was then determined through visual interpretation of the original Landsat imagery. Confusion matrices were constructed by comparing the extracted water masks against these reference points, and the overall accuracy (OA) and Kappa coefficient were calculated using Equations (1) and (2).

The overall accuracy (OA) and Kappa coefficient were calculated using confusion matrices. Visual interpretation of Landsat imagery was used as reference data to assess extraction accuracy.

$$OA = \left(\frac{n}{N}\right) \times 100\% \quad (1)$$

where n represents the number of correctly classified samples, and N denotes the total samples.

$$Kappa = \frac{N \sum_{i=1}^n x_{ii} - \sum_{i=1}^n (x_{i+} x_{+i})}{N^2 - \sum_{i=1}^n (x_{i+} x_{+i})} \quad (2)$$

where N is the total number of samples, $\sum_{i=1}^n x_{ii}$ is the sum of the diagonal elements of the confusion matrix, x_{i+} is the sum of elements in the i -th row (representing the total number of samples belonging to class i), and x_{+i} is the sum of elements in the i -th column (representing the total number of samples predicted as class i).

2.3.3. Lake Area Dynamic Degree

The lake area dynamic degree (K) quantifies the intensity of interannual lake area changes. It is defined as the annual relative rate of change in lake area during the study period [44].

$$K = \frac{U_b - U_a}{U_a} \cdot \frac{1}{T} \times 100\% \quad (3)$$

where K denotes the dynamic degree; U_a and U_b are lake areas in a given year (e.g., year t) and the adjacent year (e.g., year $t + 1$), respectively; and T represents the study period. When $K > 0$, it indicates lake area expansion; otherwise, it indicates shrinkage. The absolute value of K reflects the intensity of lake area change.

2.3.4. Pearson Correlation Analysis

Pearson correlation analysis was employed to examine the linear correlation degree between lake area and driving factors [45].

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (4)$$

where r denotes the Pearson correlation coefficient; X_i and Y_i represent lake area and the corresponding driving factor in year i , respectively; and $\bar{X}$ and $\bar{Y}$ are the average values of lake area and the driving factor; n is the sample size.

2.3.5. Ridge Regression Analysis

Multicollinearity among independent variables was examined using the Variance Inflation Factor (VIF). Ridge regression is effective in improving the stability of parameter estimation under multicollinearity conditions [46]. Ridge regression introduces an L2 regularization penalty term to shrink the magnitude of correlated variable coefficients, avoiding extreme coefficient fluctuations caused by high inter-variable correlation and producing interpretable, stable outputs for comparative driver attribution. In this study, ridge regression was adopted to quantitatively identify the driving mechanisms of lake area change in Ebinur Lake and to address potential multicollinearity among driving factors [47,48].

The objective function of the ridge regression model is expressed as

$$\min \left[\sum_{i=1}^n (Y_i - \beta_0 - \sum_{j=1}^k \beta_j X_{ij})^2 + \lambda \sum_{j=1}^k \beta_j^2 \right] \quad (5)$$

where Y_i is lake area (km^2), X_{ij} denotes the j -th driving factor of the i -th sample, β_j is the regression coefficient, λ is the penalty parameter, and n and k represent the sample size and the number of independent variables, respectively.

Independent variables were standardized using Z-score normalization, while lake area retained its original units. Regression coefficients thus represent lake area change induced by one-standard-deviation variation in each factor. To ensure consistency between prediction and goodness-of-fit assessment, R^2 was calculated based on datasets in which both dependent and independent variables were standardized.

Based on the standardized ridge regression coefficients, the sign of each coefficient indicates the direction of influence, while its absolute value reflects the strength of impact. The relative contribution of each driving factor to lake area change was calculated as follows:

$$\text{Contribution } (\%) = \frac{|\beta_i^*|}{\sum_{i=1}^5 |\beta_i^*|} \quad (6)$$

where $|\beta_i^*|$ denotes the absolute standardized regression coefficient of the i -th independent variable, and $\sum_{i=1}^5 |\beta_i^*|$ is their sum.

The overall methodological workflow of data processing, water extraction, spatio-temporal dynamics detection and driving force quantification is illustrated in Figure 2.

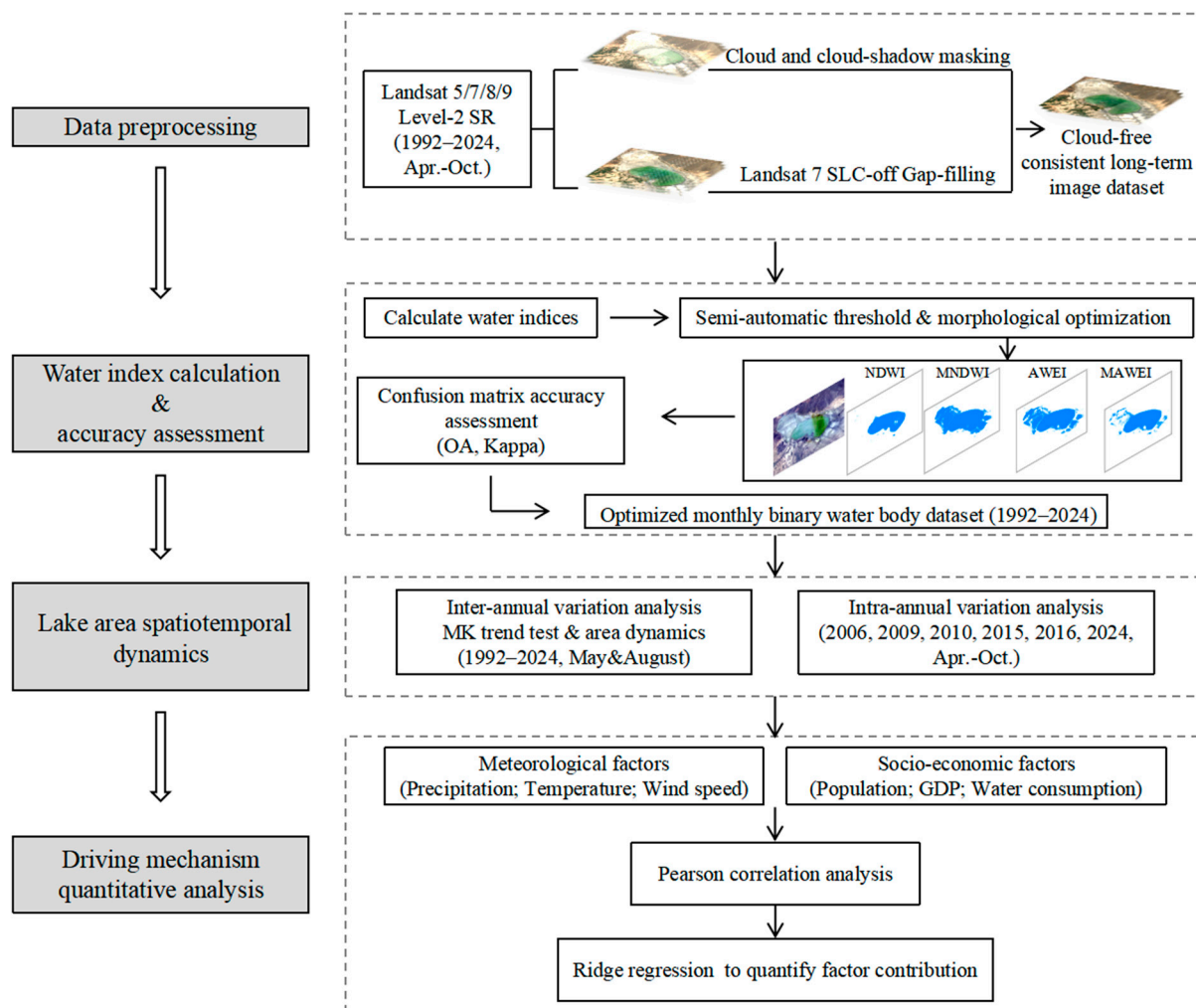


Figure 2. Research framework.

3. Results

3.1. Water Extraction Results and Accuracy Assessment

Ebinur Lake's areas in June 1994, 2004, 2014, and 2024 were extracted using NDWI, MNDWI, AWEI, and MAWEI, and the results were compared (Figure 3). Overall, all four indices were capable of distinguishing water bodies from non-water surfaces. However, clear differences were observed in boundary delineation and sensitivity to dried lakebeds. Among them, NDWI produced the clearest lake boundaries, followed by MAWEI, whereas MNDWI and AWEI showed lower sensitivity to lake margins and dried lake areas, resulting in noticeably blurred edges.

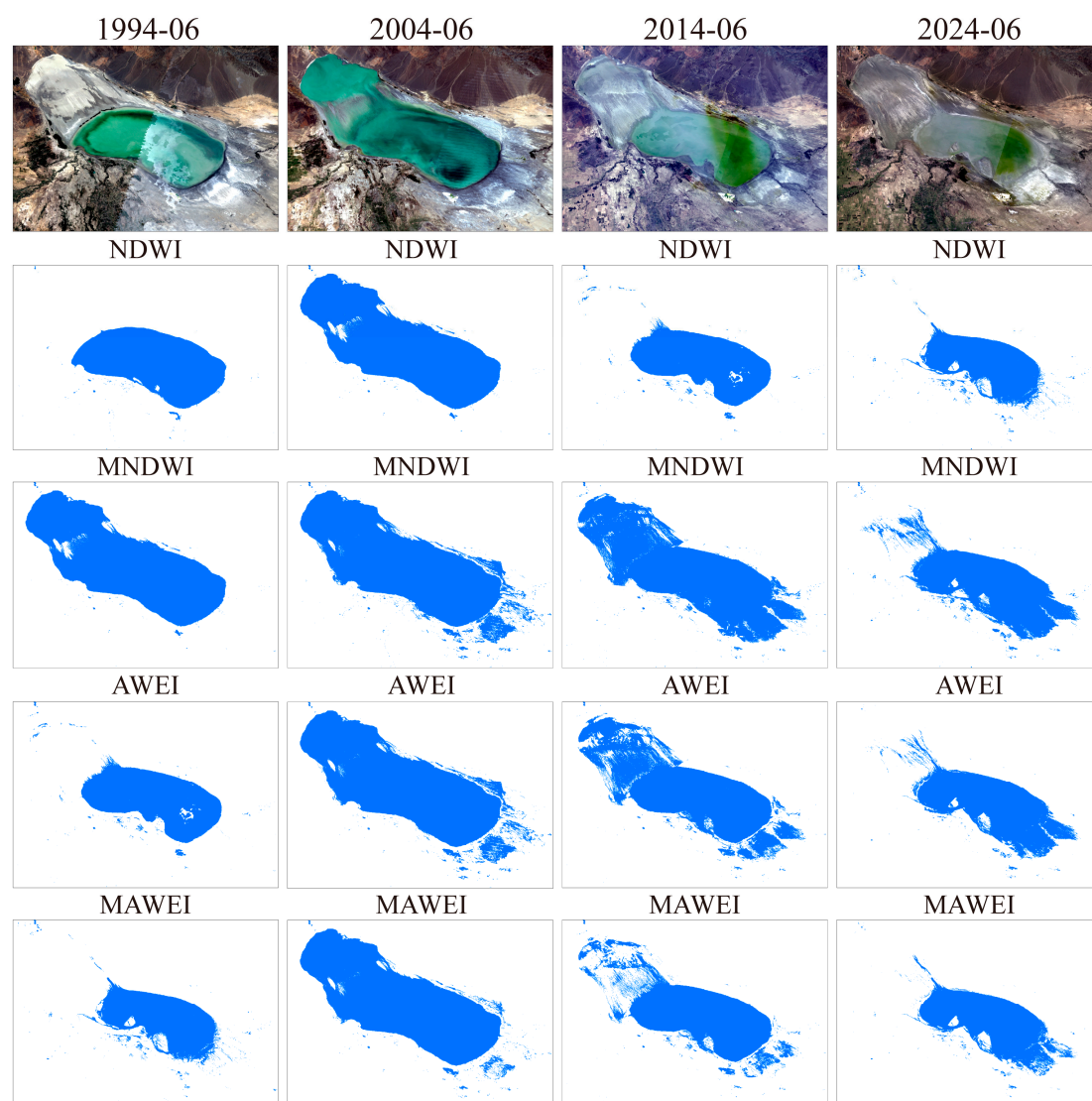


Figure 3. Water body extraction results of NDWI, MNDWI, AWEIsh, and MAWEI for Ebinur Lake in June 1994, 2004, 2014, and 2024.

Confusion matrix-based accuracy assessment indicates that the overall accuracy (OA) of all four indices exceeded 90% (Table 3), demonstrating generally good classification performance. NDWI achieved the highest accuracy, with OA values exceeding 97%, and reached 98.78% in both 1994 and 2004. MAWEI ranked second, with OA values above 95%. AWEI exhibited OA values above 91%. MNDWI maintained OA values above 90%. Notably, all indices achieved their highest classification accuracy in 2004, which may be related to the relatively high quality of the Landsat imagery for that year. Considering both overall accuracy and Kappa coefficient values, the average classification performance of the four indices ranked as NDWI > MAWEI > MNDWI > AWEI.

Table 3. Interannual accuracy assessment of water extraction indices.

		NDWI	MNDWI	AWEI	MAWEI
June 1994	OA (%)	98.78	92.68	91.46	95.12
	Kappa (%)	97.26	84.32	81.87	89.36
June 2004	OA (%)	98.78	96.34	95.12	98.78
	Kappa (%)	97.56	92.69	90.26	97.56
June 2014	OA (%)	97.18	91.55	90.14	95.77

June 2024	Kappa (%)	93.71	81.93	79.14	90.67
	OA (%)	97.14	90.00	91.43	95.71
	Kappa (%)	91.07	72.44	76.92	87.60

To further evaluate the temporal stability of different water indices at the intra-annual scale, imagery from April to October 2024 was used for extraction accuracy (Table 4). The results show marked differences in performance among indices across months. NDWI maintained consistently high and stable accuracy throughout the year (OA: 95.12–97.14%; Kappa coefficients: 82.85–91.07%). MAWEI achieved relatively high accuracy during certain months, particularly from June to August, but its overall stability was lower than that of NDWI. In contrast, MNDWI and AWEI exhibited pronounced month-to-month variability, with notably lower Kappa coefficients during periods of reduced lake area or complex shoreline conditions.

Table 4. Intra-annual accuracy assessment of water extraction indices (2024).

		NDWI	MNDWI	AWEI	MAWEI
April 2024	OA (%)	96.25	88.73	91.30	93.15
	Kappa (%)	83.56	66.82	71.91	74.28
May 2024	OA (%)	95.12	88.10	90.24	92.68
	Kappa (%)	82.85	66.24	72.80	77.76
June 2024	OA (%)	97.14	90.00	91.43	95.71
	Kappa (%)	91.07	72.44	76.92	87.60
July 2024	OA (%)	96.34	87.80	87.80	95.12
	Kappa (%)	84.87	73.60	70.55	82.79
August 2024	OA (%)	96.34	87.80	89.02	93.90
	Kappa (%)	90.56	71.55	73.92	86.78
September 2024	OA (%)	96.34	90.24	90.24	92.68
	Kappa (%)	85.88	71.92	67.40	74.16
October 2024	OA (%)	96.34	83.33	84.72	90.24
	Kappa (%)	86.70	64.94	69.44	80.01

In summary, NDWI provides the highest extraction accuracy and temporal stability under the high-salinity and strong-interference conditions of Ebinur Lake. Consequently, NDWI was selected as the optimal water extraction method for subsequent analyses of lake area dynamics.

3.2. Lake Area Dynamics

3.2.1. Interannual Variations

To characterize interannual variations in lake area, imagery selected in May and August 1992–2024 was used to extract lake area based on NDWI (Figure 4a). Over the study period, the average lake area in May and August was 635.64 km² and 515.67 km², respectively, with the May area being approximately 1.23 times that of August. In terms of temporal changes, lake area exhibited an overall fluctuating downward trend. Specifically, the lake area in May decreased from 551.49 km² in 1992 to 344.20 km² in 2024, representing a total reduction of 207.29 km² (37.58%) at a rate of 6.48 km²·a^{−1}. In August, lake area declined from 509.05 km² in 1992 to 240.96 km² in 2024, corresponding to a total reduction of 268.09 km² (52.66%) and a faster decline rate of 8.37 km²·a^{−1}. The reduction in lake area and the reduction rate in August were markedly greater than those in May. The maximum lake area in both months occurred in 2003 (May: 975.86 km²; August: 855.67 km²), whereas the minimum values were recorded in 2023 (May: 328.51 km²; August: 136.00 km²).

Overall, lake area remained relatively stable prior to 1997, followed by a slight decline in 1997 and a subsequent recovery until 2000. After 2000, the downward fluctuation

trend became more pronounced, characterized by three peak years (2003, 2012, and 2017) and three trough years (2009/2010, 2015, and 2023). During the period from 2009 to 2017, the interval between peaks and troughs shortened to 2–3 years. Although the transitions from peak to trough during 2003–2009 and 2017–2023 both spanned approximately six years, the peak surface area in 2017 (May: 910.77 km²; August: 722.35 km²) was substantially lower than that in 2003, and the trough value in 2023 represented the lowest lake area over the entire study period. The above shows that the fluctuation trend of the lake area of Ebinur Lake is particularly obvious from 2009 to 2017; the fluctuation cycle is shortened, and the area of the peak and valley has a significant decreasing trend. Analysis of the annual lake area dynamic degree (K) (Figure 4b) further reveals an increasing trend in the absolute values of K for two months, particularly during peak and trough years. It further confirms continuous degradation of lake area [49]. The absolute values of K in August were consistently higher than those in May, suggesting a faster rate of interannual change in August, which is consistent with the higher reduction rate observed in the August lake area.

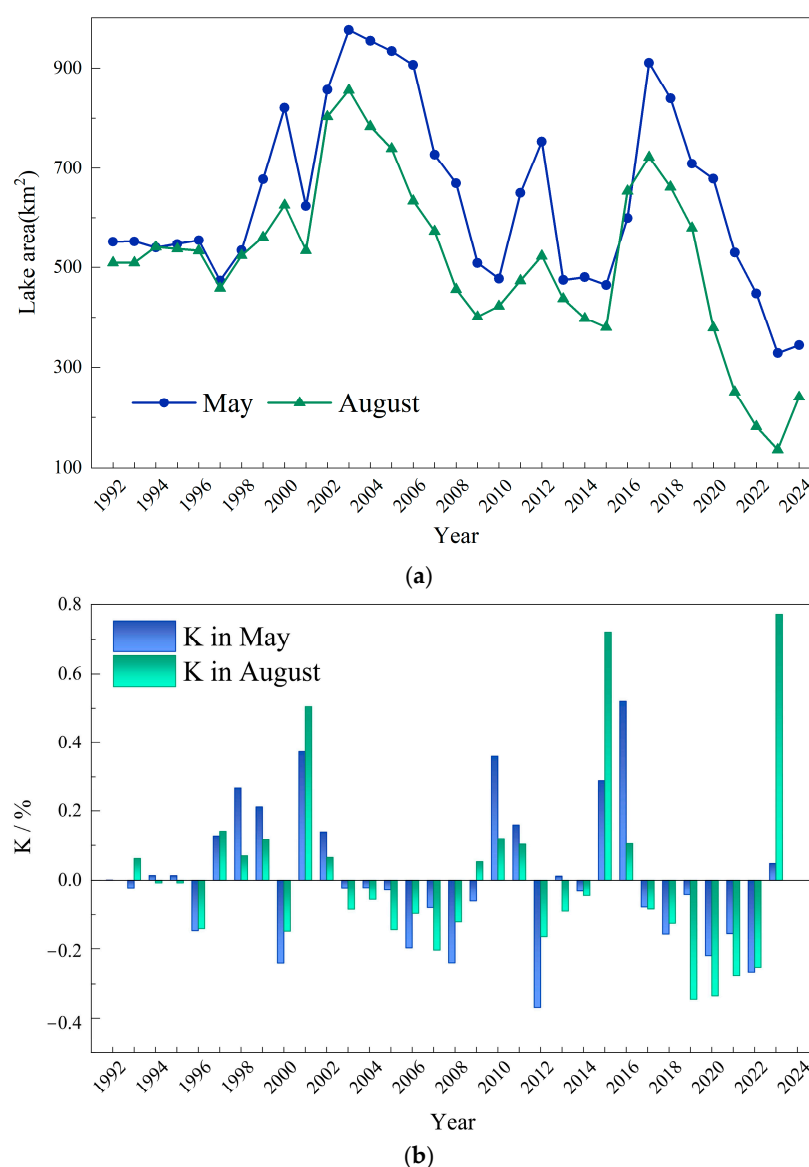


Figure 4. Interannual variations in lake area of Ebinur Lake in May and August (1992–2024): (a) lake area in May and August; (b) interannual dynamic degree.

To examine whether abrupt change points occurred in the interannual lake area series, the Mann–Kendall test was applied. The results show that the UF and UB curves for both May and August did not intersect within the 95% confidence interval (Figure 5), indicating the absence of statistically significant abrupt change points during the study period. Despite clear differences in fluctuation characteristics among different phases, these variations primarily reflect short-term oscillations rather than persistent trend shifts. Overall, interannual lake area change in Ebinur Lake is best characterized as a fluctuating downward trend without abrupt change points, rather than a stepwise transition.

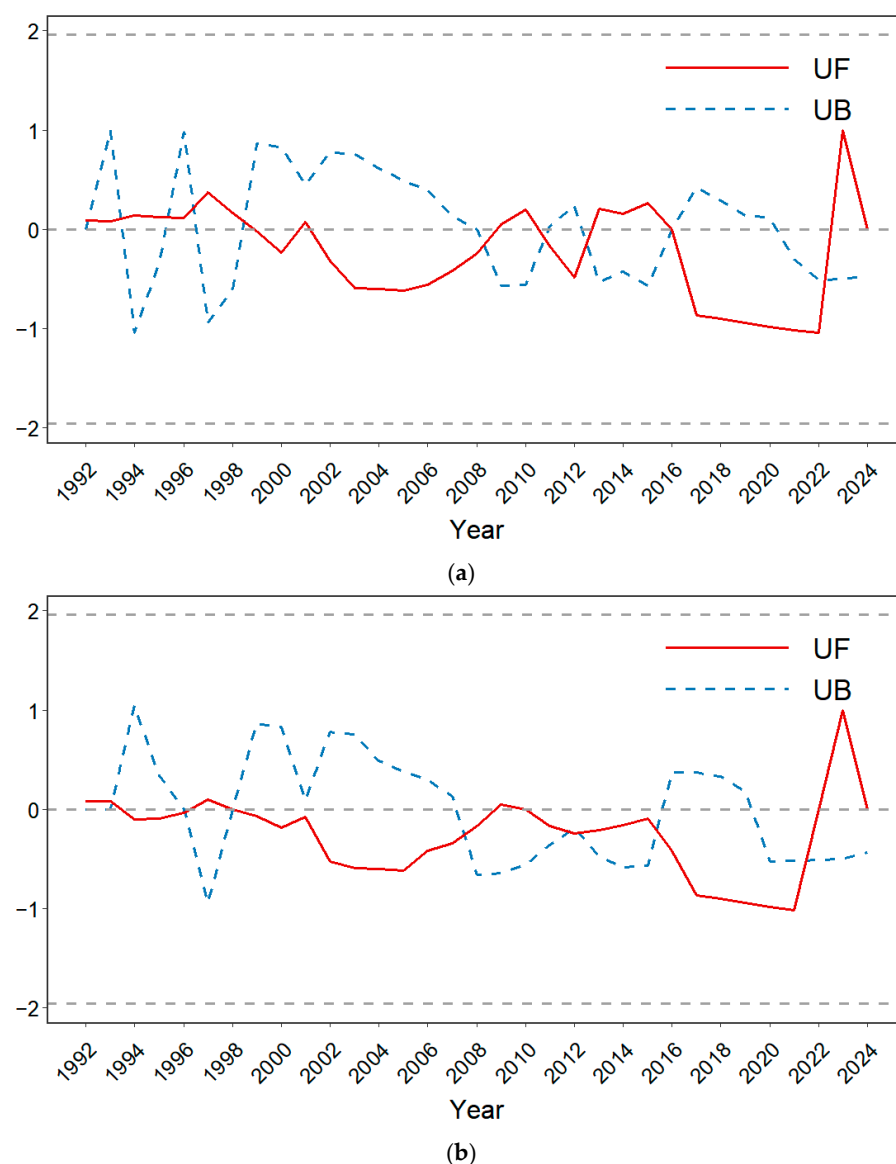


Figure 5. Mann–Kendall test results for interannual lake area variations in Ebinur Lake: (a) May; (b) August.

3.2.2. Intra-Annual Variations

To characterize intra-annual variations in lake area, this study selected six years, including 2006, 2009, 2010, 2015, 2016, and 2024, and analyzed the monthly variation characteristics of surface area during the growing season from April to October (Figure 6). A consistent “first decrease, then increase” pattern emerged across most years: In April–May, the lake area showed irregular changes in slight increase or decrease; the continuous decreasing trend after May to August or September, which is the minimum value of the lake area in the growing season; at the end of the growing season in October, the irrigation

period ended, and the lake area showed a slight increase. Linear fitting indicated an overall downward trend during the growing season (April–October) for most selected years. In terms of change rate, monthly lake area change rates showed substantial variability. Across all study years, the average monthly change rate during the growing season ranged from -67.55 to $9.92 \text{ km}^2\cdot\text{month}^{-1}$, with a mean value of $-22.32 \text{ km}^2\cdot\text{month}^{-1}$. Among all years, 2006 exhibited the most rapid lake area shrinkage, with a monthly decrease rate of $-67.55 \text{ km}^2\cdot\text{month}^{-1}$. In contrast, lake area shrinkage in 2010 was relatively moderate, with a monthly change rate of $-4.89 \text{ km}^2\cdot\text{month}^{-1}$. Notably, 2016 was the only year among the selected years in which lake area exhibited an increasing trend during the growing season, with an average monthly expansion rate of $9.92 \text{ km}^2\cdot\text{month}^{-1}$. Combined with precipitation observations from the Jinghe meteorological station for the corresponding period, it is evident that annual precipitation in 2016 reached 201.7 mm , which was significantly higher than the long-term mean annual precipitation (90.9 mm). This suggests that extreme precipitation substantially increased winter snow accumulation in mountainous areas and enhanced summer river runoff, thereby increasing inflow to Ebinur Lake and supporting the observed expansion of lake area.

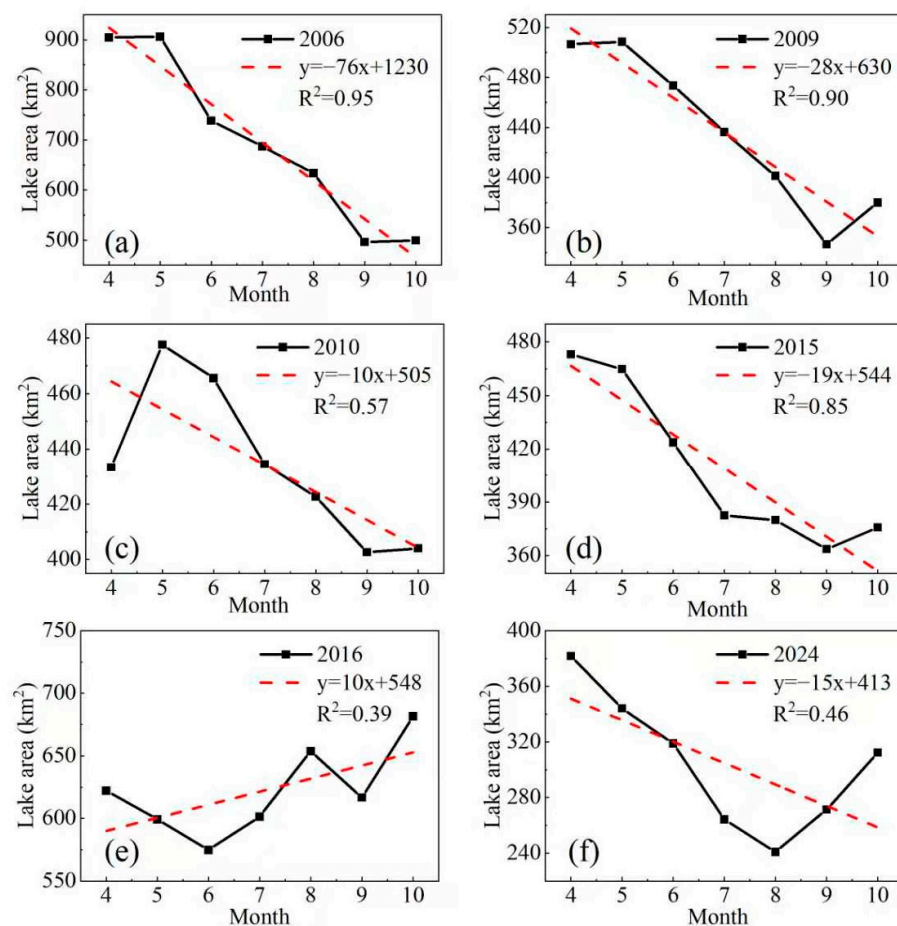
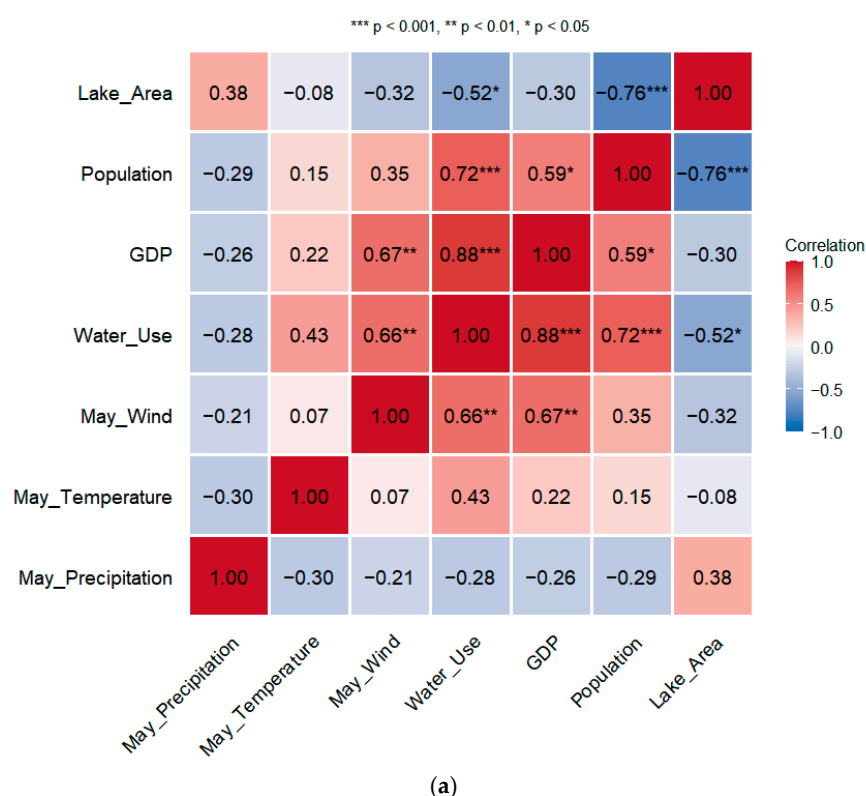


Figure 6. Intra-annual variations in Ebinur Lake area for representative years ((a) 2006, (b) 2009, (c) 2010, (d) 2015, (e) 2016, (f) 2024).

3.3. Driving Mechanism Analysis

3.3.1. Pearson Correlation Between Lake Area and Driving Factors

Based on the common years (2004–2021) across datasets, Pearson correlation analysis was conducted to investigate the driving mechanisms of meteorological factors (monthly precipitation, monthly average temperature, and monthly maximum 10 min average wind speed) and socio-economic factors (population, GDP, and annual water consumption) on the interannual variations in Lake area in May and August (Figure 7). The results indicate that, in both May and August, lake area is negatively correlated with population, water consumption, and GDP. Among these variables, population is the strongest correlation with lake area (May: $r = -0.76$; August: $r = -0.77$, $p < 0.001$), followed by water consumption (May: $r = -0.52$; August: $r = -0.57$, $p < 0.05$). The correlation with GDP is relatively weak (May: $r = -0.30$; August: $r = -0.38$, $p > 0.05$). In contrast, correlations between lake area and meteorological factors are generally insignificant ($p > 0.05$). Lake area shows a positive correlation with precipitation (May: $r = 0.38$; August: $r = 0.10$), while negative correlations are observed with temperature (May: $r = -0.08$; August: $r = -0.25$) and wind speed (May: $r = -0.32$; August: $r = -0.04$). These results suggest that population growth and socio-economic development have intensified water resource consumption, thereby reducing river runoff and inflow to the lake and contributing to lake area shrinkage. In terms of statistical significance, socio-economic factors play a dominant role in lake area change, particularly population growth and increased water consumption, whereas meteorological factors exert a comparatively weaker regulating effect.



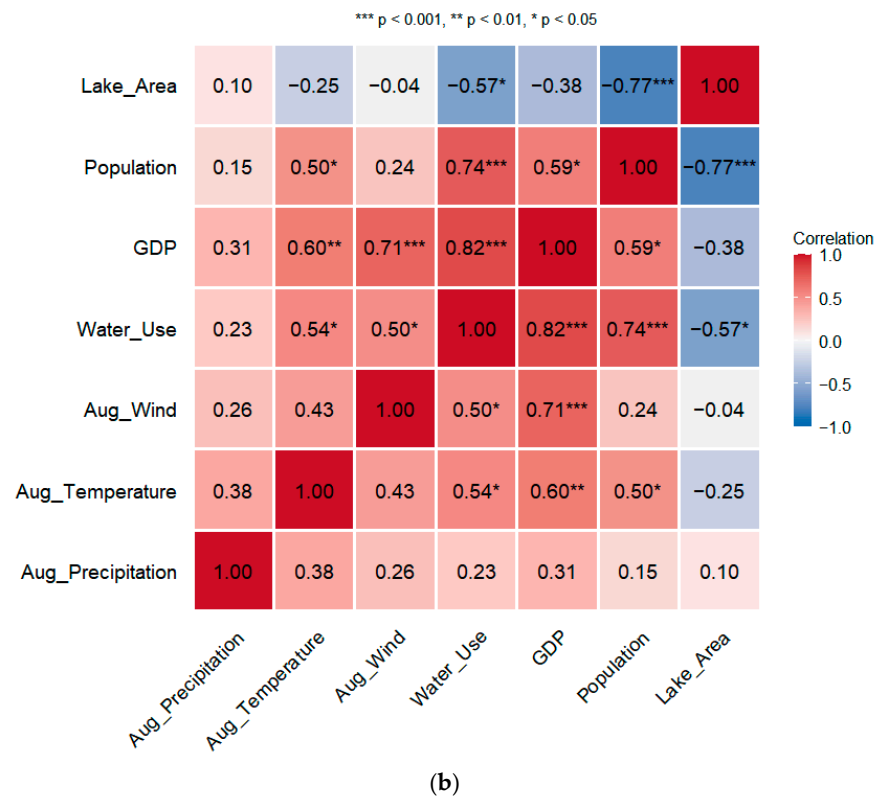


Figure 7. Correlation between lake area and driving factors ((a): May; (b): August).

From the perspective of correlations among driving factors, socio-economic variables exhibit significant coherence in both May and August. Population, water consumption, and GDP are all significantly positively correlated with each other. Water consumption shows an extremely significant positive correlation with GDP (May: $r = 0.88$, $p < 0.001$; August: $r = 0.82$, $p < 0.001$) and population (May: $r = 0.72$, $p < 0.001$; August: $r = 0.74$, $p < 0.001$). Correlations among meteorological factors and between meteorological and socio-economic factors exhibit clear monthly differences. For example, average annual temperature is significantly positively correlated with water consumption ($r = 0.54$, $p < 0.05$) and GDP ($r = 0.60$, $p < 0.01$) in August, whereas no significant correlations are observed in May ($p > 0.05$). These results indicate that although meteorological factors do not directly exert a significant linear influence on lake area change, they may indirectly affect the lake system by modulating human water use behavior and socio-economic activities.

3.3.2. Ridge Regression Results

To further quantify the driving mechanisms of lake area change, ridge regression models were constructed with lake area in May and August as dependent variables and population, GDP, annual water consumption, monthly precipitation, monthly average temperature, and monthly maximum 10 min average wind speed as independent variables. The models show good explanatory performance (May: $R^2 = 0.675$; August: $R^2 = 0.659$). The contribution ratios of each factor were calculated based on the absolute values of standardized ridge regression coefficients (Table 5). The results indicate that, in May, the contribution of driving factors ranks as follows: population (37.80%) > GDP (21.77%) > water consumption (15.77%) > monthly precipitation (11.97%) > wind speed (6.82%) > monthly average temperature (5.88%). In August, the ranking changes to population (49.69%) > water consumption (16.23%) > monthly precipitation (13.34%) > wind speed (12.64%) > monthly average temperature (4.75%) > GDP (3.35%). Population, water consumption, and monthly precipitation are the three most influential factors affecting lake

area change. However, the contribution of GDP shows pronounced seasonal differences: it ranks second in May (21.77%) but decreases substantially to only 3.35% in August. Population and water consumption exert relatively strong influences, and their effects on lake area are negative in both May and August. Among meteorological factors, monthly precipitation shows a relatively clear positive influence on lake area change, whereas the effects of monthly average temperature and wind speed are comparatively weak. Overall, socio-economic factors dominate lake area change, accounting for approximately 70% of the total contribution, while meteorological factors play a weaker regulating role, contributing about 30%.

Table 5. Contribution of driving factors based on ridge regression.

Driving Factors		Standardized Ridge Regression Coefficient		Absolute Value of Coefficient		Contribution (%)	
		May	August	May	August	May	August
Socio-economic factors	Population	−105.66	−90.16	105.66	90.16	37.80	49.69
	GDP	60.85	−6.07	60.85	6.07	21.77	3.35
	Water consumption	−44.07	−29.46	44.07	29.46	15.77	16.23
Meteorological factors	Monthly precipitation	33.45	54.21	33.45	24.21	11.97	13.34
	Monthly average temperature	16.43	8.62	16.43	8.62	5.88	4.75
	Wind speed *	−19.07	22.94	19.07	22.94	6.82	12.64

Note: *: wind speed denotes the monthly maximum 10 min average wind speed.

4. Discussion

4.1. Applicability of Water Indices for Lake Area Extraction in Arid Inland Terminal Saline Lakes

Ebinur Lake is a typical hypersaline terminal lake dominated by wide expanses of bare salt crust and uniform dry lakebed, which creates unique salt-induced spectral interference that differentiates water index performance from that in freshwater or urban watersheds. The NDWI, constructed from green and near-infrared bands, reliably separates open water from exposed salt flats and barren lakebed [50]. The spectral contrast between water and salt-crust surfaces is sufficiently captured by green/NIR combinations to suppress salt-crust misclassification, which constitutes the core spectral advantage of NDWI in hypersaline lake environments. The relatively uniform background minimizes the risk of spectral confusion, allowing NDWI to maintain consistent performance across different seasons and sensors. Numerous studies confirm NDWI performs well in open-water extraction and is suitable for inland saline lakes without complex background interference, such as Ebinur Lake [39,50,51].

In contrast, MNDWI replaces the near-infrared band with shortwave infrared (SWIR) bands to mitigate urban building interference [40], yet it yields lower extraction accuracy at Ebinur Lake. SWIR band is highly sensitive to dry saline-alkali land and lakeshore sediments. In the hypersaline environment of Ebinur Lake, the exposed salt-crust beds and lakeshore sediments exhibit high SWIR reflectance, which reduces the spectral contrast between water and the salt-covered non-water background. It causes misclassification and water boundary fragmentation, consistent with the lower extraction accuracy of MNDWI

observed in this study [52–54]. Although MNDWI is effective at suppressing urban background interference, its SWIR-based formulation is less suited to the high-salinity setting of Ebinur Lake.

AWEI and MAWEI are multi-band indices developed to resolve mixed shadow and complex mountain/urban land cover, with additional band constraints to separate water from buildings and vegetation [42,55]. However, in regions with relatively uniform backgrounds like Ebinur Lake, the advantages of multi-band formulations are limited. The added spectral constraints may introduce unnecessary sensitivity to local substrate variations, reducing the stability of water boundary extraction compared to the simpler NDWI formulation.

Collectively, the index comparison reveals a clear scene-dependent performance rule for water extraction algorithms. For hypersaline arid terminal lakes with widespread bare salt crusts and low-diversity background surfaces, simple two-band indices like NDWI minimize salt-related spectral disturbance and shoreline fragmentation, which fundamentally explains its superior performance relative to MNDWI, AWEI and MAWEI in this study. This further suggests that, although water indices tend to become increasingly complex and exhibit strong scene dependency, simpler indices may outperform more complex ones in specific environments due to their stability and high discrimination between dominant land-cover types, particularly water and bare surfaces [56–58].

4.2. Characteristics and Driving Mechanisms of Lake Area Change in Ebinur Lake

Faster lake shrinkage in August than May reflects peak agricultural irrigation and intensified human water consumption [59,60]. Interannual variation is linked not only to climatic variability and increasing water-use intensity but also to phased basin policy intervention. Previous studies show policies including the national government's Grain for Green policy launched in 2000 and ecological protection plans implemented in 2018 temporarily alleviated lake degradation [20]. However, renewed lake area decline after 2018 suggests that long-term stabilization requires more sustained and robust integrated management.

Intra-annually, its changing pattern corresponds well with the basin's hydrological regime of spring snowmelt recharge; summer high consumption; relative autumn stabilization [59]. Notably, 2016 was an exceptionally high-precipitation year, during which lake area showed a slight increasing trend throughout the growing season. This indicates that extreme precipitation can enhance mountain snow accumulation and river runoff, thereby increasing inflow to the lake and temporarily supporting lake expansion, consistent with previous findings on meteorologically driven anomalies in Ebinur Lake [59]. However, such meteorologically driven expansion represents only short-term fluctuations and does not alter the long-term declining trend, nor does it challenge the dominant role of human activities in lake evolution. A further comparison of intra-annual shrinkage rates indicates far more pronounced lake area shrinkage in 2006 relative to other years; this year saw a rapid declining phase [26], which likely amplified water consumption during the growing season.

Throughout the study period, driving mechanism results were consistent with previous studies indicating that human activities exert a more direct influence on the ecological health and biodiversity of saline lakes than climate change [61]. The seasonal divergence of socio-economic driving intensity between May and August is fundamentally governed by the unique single-crop agricultural production cycle of the Ebinur Lake basin, where irrigation water demand varies drastically across growing stages and reshapes the relative contribution of each human-related factor. Ridge regression results quantitatively capture seasonal differentiation, with the contribution of population in August being markedly higher than in May, reflecting the amplified effect of population size under the combined pressures of agricultural irrigation and domestic water demand during the

peak growing season [29]. Water consumption maintained a stable and significant contribution in May and August, underscoring its role as a direct consumption factor that did not change significantly with the month. The positive contribution of GDP in May indicates that economic growth, under relatively stable population and water demand, may promote ecological protection investments (e.g., water-saving irrigation and Ecological Water Transfer Projects), thereby generating positive feedback on the lake [62]. In contrast, its significantly lower contribution in August suggests that GDP influences lake area more indirectly through population size and water-use behavior, as massive summer irrigation demand offsets the positive ecological regulatory effects brought by economic investment. Within this seasonal cascade, water consumption acts as the proximate driver directly depleting lake inflow, population determines the baseline demand that becomes most apparent under water stress, and GDP modulates the system primarily through long-term investments in water efficiency and economic structure. This finding underscores the interactive relationship between economic development and environmental protection, highlighting the importance of ecological conservation and sustainable management in arid regions [63].

Meteorological factors played a comparatively minor role in driving lake area change. Wind speed contribution increased from 6.82% in May to 12.64% in August, indicating that the combined effects of high summer temperatures and strong winds can substantially enhance evaporative water loss [59]. Although precipitation and temperature exhibited clear seasonal differences in contributions, their direct effects on lake surface area remained limited. Negative correlations observed in May shifted to positive correlations in August, reflecting the typical regional climate pattern in Xinjiang: spring precipitation is often associated with cold air incursions and lower temperatures, whereas August is dominated by subtropical high-pressure systems, under which high temperatures and precipitation tend to occur concurrently [13,64].

4.3. Uncertainties and Future Perspectives

Although this study clarifies the spatiotemporal variation patterns and driving mechanisms of Ebinur Lake's area, several uncertainties and limitations remain. Early remote sensing imagery (1992–1999) was affected by sensor limitations and cloud contamination, with some lake area values relying on interpolation. Socio-economic variables derived from statistical yearbooks did not fully capture spatial heterogeneity within the basin, and hydrological variables such as groundwater extraction and reservoir regulation were not included due to data constraints. Future studies could integrate higher-resolution remote sensing imagery and ground observation data to better resolve small or fragmented water bodies, while advanced data-driven approaches may further enhance water extraction accuracy and driving mechanism quantification and elucidate the coupling between lake surface area dynamics and internal water quality changes.

5. Conclusions

Based on the Google Earth Engine (GEE) cloud platform and Landsat imagery, this study investigated area spatio-temporal variations in lake area and driving mechanisms from 1992 to 2024 in Ebinur Lake. The main conclusions are as follows:

- (1) Lake surface area was extracted using multiple water indices. NDWI maintains consistently high and stable classification accuracy across different years and multiple months within a year, outperforming MNDWI, AWEI, and MAWEI. NDWI is therefore suitable for long-term monitoring in this high-salinity and high-interference arid inland saline lake.

- (2) From 1992 to 2024, Ebinur Lake's area exhibited an overall fluctuating decline without abrupt change points, indicating continuous lake degradation [49]. Both decline magnitude and rate were greater in August than in May, reflecting the combined effects of peak agricultural irrigation and intensified human water consumption. Within the growing season (April–October), lake area generally followed a decline-recovery pattern, with larger areas at the beginning of the growing season than at its end, and minimum values occurring during the peak irrigation period (August–September).
- (3) Socio-economic factors dominated lake area changes, while meteorological factors played a secondary regulatory role. Among socio-economic drivers, population growth and water consumption exert the strongest influences, with their effects intensifying during the summer irrigation season. The seasonal contrasts in driving intensities are fundamentally governed by the basin's single-crop agricultural production cycle, which reshapes the relative contribution of each human-related factor across growing stages.

Future ecological protection and management of Ebinur Lake should prioritize improving water-use efficiency and optimizing industrial structure, supported by strict water resource management to alleviate long-term lake shrinkage. Furthermore, the cross-sensor calibration and monthly scale quantitative driving decomposition framework constructed in this work is not limited to Ebinur Lake. The complete data processing and seasonal attribution workflow can be widely applied to other closed-basin inland salt lakes with salt-crust settings, providing a replicable analytical paradigm for long-term intra-annual eco-hydrological monitoring of arid saline lakes in Central Asia and northwest China.

Author Contributions: Conceptualization and methodology, X.W., D.N. and X.C.; software, validation, formal analysis, resources, data curation, writing—original draft preparation and visualization, X.W.; investigation, Y.L., J.H., X.J., Z.H., C.Y. and Y.Z.; writing—review and editing, supervision, project administration, funding acquisition, X.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Key R&D Projects in Xinjiang Autonomous Region (2024B03025-1), the Science & Technology Fundamental Resources Investigation Program (Grant NO. 2023FY100703).

Data Availability Statement: The data that support the findings of this study will be made available by the authors upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

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