

Article

Hydrological Evolution of Siling Co over the Past 38 Years: Lake Area, Water Level Monitoring, and Water Storage Estimation Based on Multi-Source Remote Sensing

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Highlights

What are the main findings?

- Siling Co experienced significant long-term expansion between 1988 and 2025, characterized by substantial increases in lake area, water level, and water storage, indicating intensified regional water accumulation under climate change;
- Lake water storage changes (LWSC) exhibited strong consistency with terrestrial water storage (TWS) variations; during 2002–2019, TWS anomalies lagged approximately one year behind LWSC, indicating a pronounced temporal delay in the hydrological regulation processes within the regional water cycle;
- The combined use of multi-source remote sensing data and GRACE/GRACE-FO observations effectively revealed the long-term coupling relationship between lake evolution and regional terrestrial water redistribution on the Tibetan Plateau.

What are the implications of the main findings?

- It is recommended to strengthen monitoring and early warning systems in response to the ongoing expansion of Siling Co;
- The one-year lag of TWS anomalies behind LWSC reflects an interannual regulation process. This process results from differences in response times among various water storage components.

Abstract

Lakes on the Tibetan Plateau are sensitive indicators of climate change. Their water storage variations play an important role in regional hydrological processes and ecological security. This study is based on multi-source remote sensing and meteorological data from 1988 to 2025. Lake area was extracted using the MNDWI and the Otsu threshold method. HYDROWEB water level data were used to establish an area-water level relationship. This relationship was then applied to reconstruct a long-term water level time-series and estimate changes in lake water storage. GRACE/GRACE-FO data and meteorological observations were further analyzed to identify the driving factors. The results show that Siling Co experienced a persistent expansion over the study period, with the lake area increasing by 805.83 km², water level rising by 14.33 m, and water storage increasing by



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30.42 km³. Correlation analysis indicates that air temperature, precipitation, and evaporation jointly influenced lake water storage variations. Among these factors, precipitation plays a relatively more important role. During 2002–2019, lake water storage changes (LWSC) were highly consistent with terrestrial water storage (TWS) variations. However, TWS anomalies lagged approximately one year behind LWSC. These findings improve the understanding of the long-term hydrological responses of Siling Co to climate change. They also provide a scientific basis for water resource management and infrastructure planning in the region.

Keywords: multisource remote sensing technology; Siling Co; temporal variation; climate change

1. Introduction

Lakes are an important component of the terrestrial hydrosphere and act as indicators of regional climate change. Changes in alpine lakes are determined by the combined effects of various factors. These factors include precipitation variability, glacier melt, permafrost degradation, climate change, and changes in TWS [1,2]. When significant climate variability occurs over a certain time scale, it alters water supply to lakes. This process leads to corresponding changes in lake morphology. Changes in lake area and water level directly reflect local topographic and geological conditions within the basin. They also indicate the evolution of regional ecological and climatic environments.

The Tibetan Plateau (TP) is the region in China with the highest density of lakes and the largest total lake area. However, due to its complex terrain and harsh environmental conditions [3], traditional in situ measurements are limited by equipment and technology. Observation sites are sparse, time-series are short, and data continuity is often insufficient. These limitations restrict scientific and sustainable water resource management. They also hinder analyses of climate change processes. This is especially true for studies on the response of high-altitude regions to global climate change. In recent decades, the TP has experienced pronounced climate changes. These changes are characterized by rising air temperature, weakening wind speed, reduced potential evaporation, and increased atmospheric moisture [4,5]. These changes have altered regional water and energy cycles. They have also affected the environment, including glaciers, permafrost, and river runoff, as well as ecosystems such as grasslands, pastoral systems, and local communities [6]. Remote sensing observations and field surveys indicate that lake area changes on the TP showed clear spatial heterogeneity from the 1970s to 2018. Lakes expanded in the central and northern regions and shrank in the south [7–11]. Further analyses suggest that this north–south contrast in lake growth is driven by the combined effects of precipitation, glacier meltwater, and changes in atmospheric circulation patterns [6,12].

Siling Co is located in the central TP. It is the largest inland lake in the Tibet Autonomous Region, and its water level has increased rapidly since the late 1990s [13,14]. Several driving factors have been identified. These include increased precipitation, enhanced glacier melt, rising air temperature, reduced potential evapotranspiration, and permafrost degradation [15–19]. Previous studies suggest that precipitation and evaporation dominate water storage variations in Siling Co [20]. As a glacier-fed lake, the contributions from glacier meltwater and permafrost degradation play a relatively minor role in the long-term trend [21,22]. Therefore, continuous monitoring of lake water storage in Siling Co is essential for clarifying climatic influences and assessing future evolution. Earthquake catalogs from the United States Geological Survey (USGS), the Global Centroid-

Moment-Tensor (CMT), and the China Earthquake Networks Center (CENC) were used in this study. These catalogs indicate that seven moderate earthquakes with magnitudes between Mw 5.0 and Mw 6.0 occurred within 200 km of Siling Co during 1988–2024 (Figure 1). This shows strong tectonic activity in the region. In addition, eleven cases of drainage reorganization were reported across the TP between 2000 and 2018 [23]. Climate change may accelerate these processes and increase the risk of glacial lake outburst floods. Since 2000, the water level of Siling Co has continued to rise. In September 2023, lake overflow from Siling Co into Bange Co occurred, damaging Provincial Road S208 between Lhasa and Shuanghu (Figure 1). Under the minimum discharge scenario, Siling Co is expected to merge with Bange Co around 2030 [24].

For Siling Co, although previous studies have conducted relatively systematic remote sensing monitoring, they still exhibit significant limitations in temporal coverage. Most multi-parameter integrated studies, which combine analyses of lake area, water level, and water storage, generally extend only up to around 2023 [25]. For instance, using multi-source remote sensing data, Wang et al. analyzed changes in lake area and inundation trends in Siling Co from 1995 to 2023, revealing a significant and continuous expansion of the lake. This expansion poses potential threats to surrounding pastoral activities and highlights the importance of monitoring lake dynamics on the TP under climate change [26]. In a separate quantitative assessment, Wang et al. reported that between 2015 and 2020, the lake area expanded at a rate of $10.3 \text{ km}^2/\text{a}$, the water level rose at approximately 0.2 m/a , and lake water storage increased at $485 \times 10^6 \text{ km}^3/\text{a}$ between 2018 and 2020 [22]. Collectively, these studies confirm that Siling Co has undergone dramatic expansion over recent decades. It has become one of the fastest-growing lakes on the TP. This has important implications for regional water resource management and climate change assessment. The JRC Global Surface Water Dataset (v1.4) is widely used for water body extraction. However, it currently covers only up to 2021. Therefore, it cannot support continuous monitoring of recent lake dynamics. These temporal gaps hinder accurate assessments of the lake's current status and future evolution trends, underscoring the urgent need to extend the monitoring time-series to the present.

The rapid development of multi-source remote sensing technologies has facilitated efficient and precise monitoring of the spatiotemporal dynamics of lakes. The application of high-resolution remote sensing imagery significantly enhances the accuracy and efficiency of lake area extraction, showcasing particular advantages in the TP region. Concurrently, substantial progress has been made in lake dynamic monitoring. Researchers have characterized spatial and temporal patterns of lakes. They have also studied the relationship between water levels and surface area, boundary information extraction, and seasonal variability. Notably, research on lake area changes and their climate-driven drivers has been particularly prominent. Ran et al. [20] used Landsat-8 and Sentinel-2 images from 2015 to 2020, combined with deep learning methods, to extract the lake shoreline. They demonstrated with GPS that the accuracy of this method was better than 30 m. Their study showed that short-term lake area changes are a rapid response to climate variability. Bai et al. [27] used Landsat remote sensing images from 1975 to 2007 to extract lake watershed boundary information based on the NDWI, and analyzed the characteristics of inland lake surface changes over the past 30 years. Liu et al. [28] used the GEE platform to extract the water bodies extent and statistically analyze the Poyang Lake area using the Otsu optimal threshold method based on the SDWI. Zhang et al. [7] used ICESat and Landsat data combined with lake elevation and area changes to study the level, area, and volume changes in the ten largest lakes in China from 2003 to 2009. The results showed that the lake water balance can be estimated quickly and effectively using remote sensing satellite data.

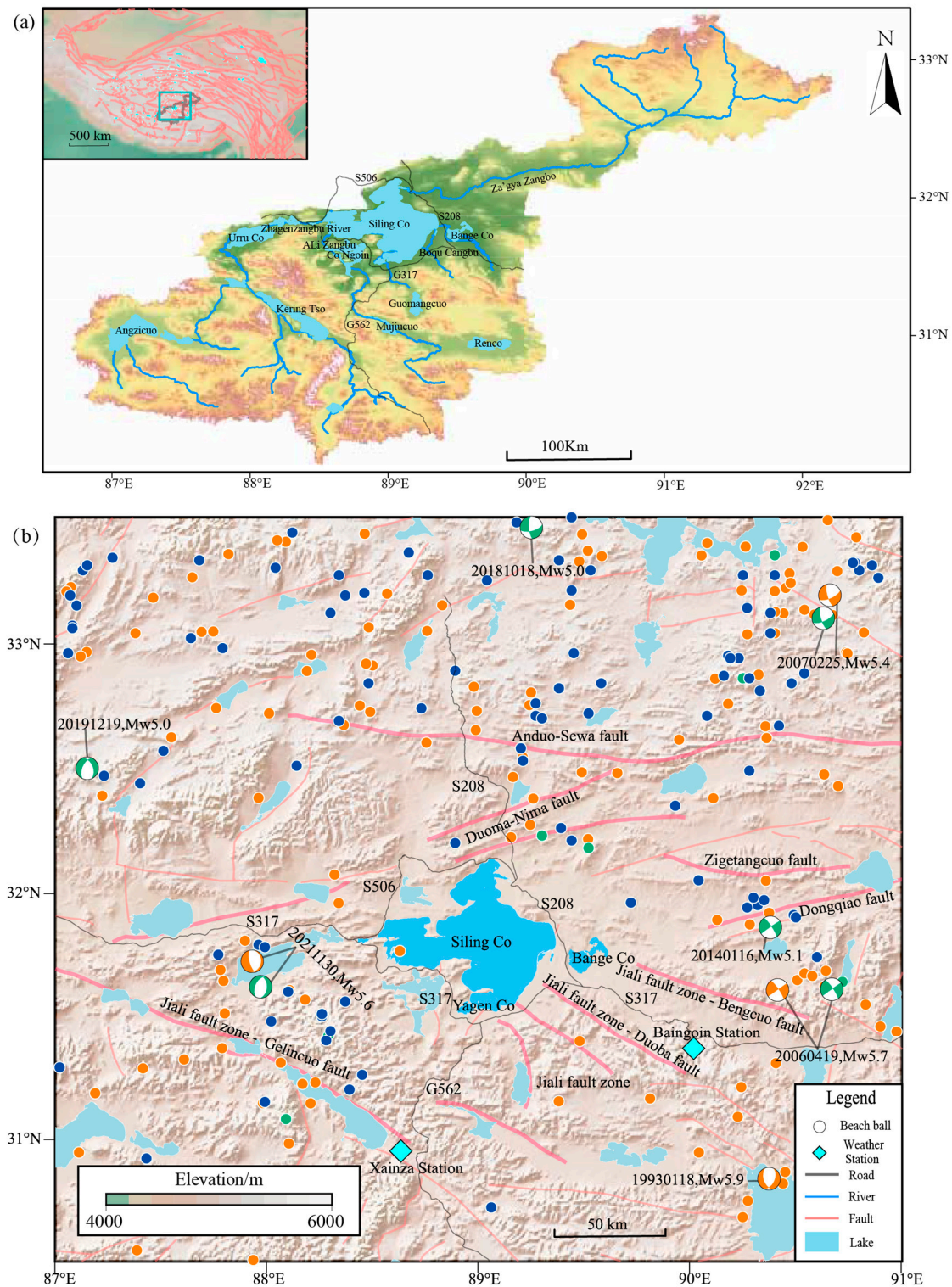


Figure 1. Geographical location of the study area. (a) Siling Co Basin Map; (b) Geological Environment Map of the Siling Co Region. In subplot (b), earthquake events with $M_w > 5.0$ (1988–2024) are indicated by the epicenter sphere, while those with $5.0 > M_w > 3.0$ are denoted by the small circle. Orange, green, and blue represent data sourced from the USGS, the GCMT and the CENC, respectively.

This study aims to systematically investigate the long-term variation and trends in the water volume of Siling Co. Using multi-source remote sensing data, we construct a long-term dataset (1988–2025) of lake water levels, area, and water storage. These datasets

are integrated with meteorological time-series to reveal lake dynamics in the context of climate change. The results enhance our understanding of regional hydrological cycle processes and support the optimization of ecological management objectives. In addition, this study provides a scientific basis for the implementation of major national projects, infrastructure planning, and the prevention and mitigation of road traffic risks.

2. Materials and Methods

2.1. Materials

2.1.1. Optical Satellite Images

The Landsat Surface Reflectance (SR) products used in this study were obtained from the Collection 2 dataset provided by the Google Earth Engine (GEE) platform. These products were preprocessed by the United States Geological Survey (USGS), which performed radiometric calibration, atmospheric correction, and geometric precision correction [29].

Radiometric calibration converts the original digital number (DN) values to top-of-atmosphere (TOA) radiance using sensor gain and bias coefficients, thereby eliminating sensor response drift errors over time. For atmospheric correction, the LEDAPS algorithm is applied to Landsat 5/7 data, while the LaSRC algorithm is used for Landsat 8/9 data. Both algorithms are based on the 6S radiative transfer model and incorporate dark target-based aerosol optical thickness retrieval along with contemporaneous water vapor and ozone auxiliary data. This process removes the effects of atmospheric scattering and absorption, converting TOA reflectance into true surface reflectance. Geometric precision correction includes two main steps. First, we performed image registration using the Global Land Survey (GLS) ground control point library and the Sentinel-2 Global Reference Image (GRI). Then, we applied orthorectification based on the SRTM 30 m or NASADEM digital elevation models (DEMs) and similar sources. All products are uniformly resampled to a fixed 30 m grid in the UTM/WGS84 coordinate system. Compared to Collection 1, Collection 2 incorporates systematic improvements in absolute radiometric calibration accuracy and geometric correction algorithms. The geometric registration accuracy, benchmarked against the Sentinel-2 GRI, achieves sub-pixel level precision. In addition, the CFmask algorithm automatically identifies and masks clouds, cloud shadows, snow, and ice pixels based on multispectral indices and thermal infrared brightness temperature, with the results recorded in the QA_PIXEL quality band.

The above systematic preprocessing workflow ensures radiometric consistency and geometric accuracy. It works well across different sensors and long time-series. This provides a reliable data foundation for conducting multi-temporal quantitative analysis in this study. The Landsat SR products have high spatial and temporal resolution and long time-series coverage. However, several limitations remain: (1) the image quality is low in some time periods due to the influence of clouds, cloud shadows, and atmospheric conditions; (2) in the high-elevation areas, such as the TP, the seasonal snow and ice cover and the shadow of mountains may interfere with the extraction of the water bodies; (3) Landsat 7 has experienced data gaps since 2003 due to the failure of the Scan Line Corrector (SLC-off).

Therefore, this study selected all spring images covering the study area from March to May during the period of 1988–2025. This selection avoids the effects of high snow and ice cover in winter and cloudy conditions in summer and autumn. After cloud removal and radiometric correction, all available images from Landsat 5/7/8 within the same time period were merged. The median composite image was generated by calculating the per-pixel median value across all bands. This process produced a cloud- and stripe-free composite that represents the period's typical surface conditions. This method significantly reduces the impacts of cloud contamination and sensor noise. To address the data gaps in

Landsat 7 SLC-off imagery [30], median filtering was first applied to reduce stripe noise. Spatial interpolation was then performed using pixel values from intact areas within the same scene. Data from Landsat 5 and 8 were also integrated to compensate for the missing stripes in Landsat 7 imagery.

Afterwards, the median composite image was then processed using a spectral water index and the Otsu automatic threshold segmentation algorithm. This automatically distinguished water bodies from non-water bodies and extracted the lake boundary. Based on the automated results, the boundary was further refined through visual interpretation. This step improved the accuracy of lake water extraction and reduced interference from mountain shadows and artificial features. Finally, the lake area was calculated by multiplying the binary image by the pixel area.

2.1.2. Lake Water Level Data

Individual altimetry satellites cover few lakes and have short service periods. Therefore, this study employed the HYDROWEB dataset to obtain a more complete water level time-series for Siling Co. The lake area derived from optical remote sensing was combined with these water level data. This enabled a more comprehensive analysis of lake dynamics, driving mechanisms, and environmental impacts.

The HYDROWEB dataset is a product of the HYDROLARE project, jointly supported by France's LEGOS laboratory and Russia's State Hydrological Institute (SHI) (<https://www.theia-land.fr/en/hydroweb/> accessed on 10 July 2026) [31]. This dataset synthesizes observations from multiple satellite altimetry missions since 1992, including ERS-1/2, TOPEX/Poseidon, GFO, Jason-1/2/3, Envisat, SARAL/AltiKa, Sentinel-3A/B, Sentinel-6A and SWOT. It offers free access to water level time-series for about 150 global lakes and reservoirs. All missions use "Ku-band radar altimetry" (wavelength about 2 cm), the width of the subsatellite footprint is between 100 and 500 m, the orbit revisit period is 10 to 35 days, and the space coverage is global. The satellite altimeter determines the water surface height by emitting microwave pulses and measuring the two-way time delay of the echo, by subtracting the altimeter range from the satellite orbit altitude. The data processing adopts the HYSOpe operational processing chain, and geophysical corrections such as wet/dry tropospheric correction and ionospheric correction are applied. Furthermore, validation against 32 in situ stations (2008–2018) shows that the dataset's average RMSE is approximately 0.70 m [32].

We used the EGM2008 geoid as the benchmark to obtain lake water level data. First, we calculated the "average lake surface" by averaging multi-period water levels along the track. Subsequent water levels were then given relative to this average value. This approach helps eliminate short-wavelength geoid errors. If the same lake is covered by multiple satellites, the lake surface water level is calculated through a three-step process: (1) the data of each satellite is processed independently; (2) using TOPEX/Poseidon data as a benchmark, the radar instrument bias and geoid differences between different satellites are eliminated; (3) the lake water level of each satellite is combined on a monthly basis.

2.1.3. GRACE Satellite Gravimetry Data

To analyze water storage changes in the Siling Co region, this study utilizes TWS anomalies data from the Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow-On (GRACE-FO) missions. The data cover the period from April 2002 to February 2025. We employ the RL06.3 v04-CRI Mascon product released by the Jet Propulsion Laboratory (JPL) [32–34]. This product applies the Coastal Resolution Improvement (CRI) filter to effectively suppress noise while preserving geophysical signals. It provides monthly gridded changes in ocean mass, ice sheets, and TWS at a spatial resolution of $0.5^\circ \times 0.5^\circ$,

expressed as equivalent water height in centimeters. A data gap exists between July 2017 and May 2018 due to the transition between GRACE and GRACE-FO missions.

The GRACE and GRACE-FO satellites measure temporal variations in Earth's gravitational field. Standard Level-3 processing includes removal of non-tidal atmospheric and oceanic signals (AOD1B product), tidal signals (FES2014, GOT4.8, IERS2010), and glacial isostatic adjustment (ICE6G-D model), along with geocentric correction, C20/C30 coefficient replacement, and ellipsoid correction. The resulting TWS anomalies, expressed as *lwe_thickness* relative to the 2004–2009 baseline, reflect integrated mass changes in soil moisture, groundwater, lakes, snow, and glaciers.

In this study, the GRACE-derived TWS data serve two purposes. First, they provide basin-scale water storage background for comparison with lake water storage variations. Second, they allow the assessment of the magnitude and trend of LWSC relative to regional TWS anomalies. This comparison helps us quantify the contribution of lake expansion to the regional water cycle.

2.1.4. Meteorological Data

We selected monthly temperature and precipitation data from two ground meteorological stations. These stations are Xainza (30.95°N, 88.633°E) and Baingoin (31.367°N, 90.017°E) (Figure 1). They are located around Siling Co. This helps analyze the climatic background of the Siling Co Basin. The data cover the period from 1988 to 2022. These data were released by the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA) through the Global Surface Summary of Day (GSOD) dataset and the Global Historical Climatology Network Monthly (GHCNm) dataset. These datasets feature complete data series, standardized quality control, and strong long-term comparability, making them widely used as fundamental data sources for regional climate background analysis. This study chose to use the GSOD dataset of two weather stations.

Xainza Station and Baingoin Station are located in the hinterland of the Northern TP. Their altitudes are about 4670 m and 4701 m, respectively. Xainza Station lies on the southwest side of the Siling Co Basin. Baingoin Station lies on the southeast side of the Siling Co Basin.

The evapotranspiration data used in this study are the monthly evapotranspiration data from 1988 to 2024, sourced from the ERA5-Land monthly reanalysis dataset released by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5-Land is driven by a land surface model and provides high-resolution land surface variables on a global scale. Its spatial resolution is $0.1^\circ \times 0.1^\circ$, corresponding to approximately 9 km. This represents a significant improvement over the original ERA5 product (0.25°) in capturing the spatial details of land surface processes.

The dataset provides total monthly actual evapotranspiration. This variable comprehensively accounts for the influence of land surface processes, including soil moisture status, vegetation cover, and surface energy balance. As a result, it can more accurately reflect the water dissipation and loss processes under the complex conditions of the plateau region.

2.2. Methodology

This study uses multispectral Landsat data spanning 1988 to 2025 to construct a 38-year lake area dataset for Siling Co. Lake water level data from the HYDROWEB dataset are used to establish a corresponding time-series. Based on the linear relationship between lake area and water level, LWSC are estimated. Combined with auxiliary data such as meteorological stations around the basin, the reasons for the change in water storage in Siling Co are comprehensively analyzed. The detailed methodology is shown in Figure 2.

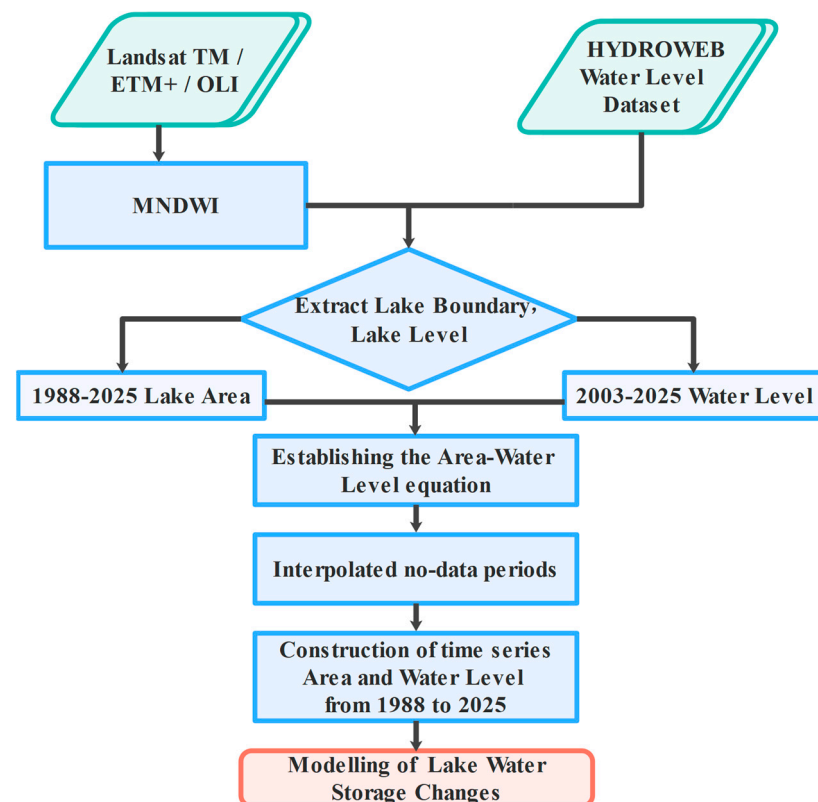


Figure 2. Research methodology flowchart.

2.2.1. Lake Extent Extraction

The traditional Normalized Difference Water Index (NDWI) extracts lake extent primarily using the green band and near-infrared band. It highlights water bodies while suppressing vegetation to extract water information from images [35]. However, the features extracted by the NDWI are often mixed with buildings and soil, leading to the overestimation of water area. To overcome this limitation, Xu proposed the Modified Normalized Difference Water Index (MNDWI), which replaces the near-infrared band with the shortwave infrared band [36]. This index significantly improves the characterization of open water features and enables the rapid and accurate separation of water and non-water features. It also largely reduces or eliminates the influence of buildings. Xu further indicated that adjusting the threshold can improve the accuracy of water classification, and optimized thresholds enable fast and accurate water classification and lake mapping. Therefore, the MNDWI has become one of the most widely used water indices. It is used across diverse applications. They also include surface water mapping, land use/land cover change analysis, and ecological studies. This is owing to its effectiveness in distinguishing water from non-water features [37–40].

This study adopts the MNDWI calculation method proposed by Xu [36], using Landsat multispectral bands at a 30 m spatial resolution. The specific band combinations are shown in Table 1. The calculation formula is given in Equation (1):

$$\text{MNDWI} = \frac{\text{Green} + \text{SWIR}}{\text{Green} - \text{SWIR}} \quad (1)$$

where Green and SWIR are the green band and short-wave infrared 1 band, respectively, as shown in Table 1. The value of the MNDWI is in the range of $[-1, 1]$, a positive value closer to 1 represents a higher possibility of water bodies.

Table 1. Band combinations used for water index calculations in the Landsat satellite series.

Satellite	Sensor	Green Band	SWIR Band	Resolution	Revisit Period
Landsat 5	TM	B2	B5	30 m	16-day
Landsat 7	ETM+	B2	B5		
Landsat 8	OLI	B3	B6		

To automate the extraction of water bodies, the Otsu automatic threshold segmentation algorithm [41] was used to segment the MNDWI images. This method searches for the optimal segmentation threshold on the grayscale histogram through the principle of maximum interclass variance. It generates a binary water body mask and automatically distinguishes between water and non-water areas:

$$\text{Water Mask} = \text{MNDWI} > T_{\text{otsu}} \quad (2)$$

where T_{otsu} is the optimal threshold obtained by computation. In the resulting binary water mask, pixels with $\text{MNDWI} > T_{\text{otsu}}$ are classified as water, while those with $\text{MNDWI} < T_{\text{otsu}}$ are classified as non-water.

The total water area within the study region is calculated by summing the water pixels in the binary image and multiplying by the pixel area. Based on the binary water image, the water–land boundary raster is converted into vector lines to obtain the lake shoreline.

To analyze interannual variations in lake area, two indicators were calculated: the interannual lake area change (ΔS) and the interannual change rate (K). The interannual lake area change represents the absolute difference in lake area between two time points and is used to quantify the magnitude of lake expansion or shrinkage. In contrast, the interannual change rate (K) represents the relative rate of change over the same period and is used to compare the intensity of lake area variations among different periods. The calculation formulas are as follows:

$$\Delta S = S_1 - S_2 \quad (3)$$

$$K = \frac{S_1 - S_2}{S_2} \times 100\% \quad (4)$$

where ΔS is the interannual lake area change; K is the interannual change rate of the lake area over a given period; and S_1 and S_2 are the lake areas at time points 1 and 2, respectively.

2.2.2. Remote Sensing Monitoring of Lake Water Level

Complete lake water level information is essential for estimating LWSC. In this study, lake water storage variations are calculated based on the linear relationship between lake area and water level. Lake water level time-series for the period 1988–2025 are constructed using two main steps [42].

(1) Annual mean water levels are calculated from existing HYDROWEB data using only data from March to May, which represents the annual lake water level. To ensure data reliability, only records with a standard deviation from height less than 0.1 m are retained;

(2) The HYDROWEB time-series lacks observations for the periods 1988–2002 and 2006, resulting in 16 years of missing data within the study period. To address this, a linear relationship between lake area and water level is established using the available HYDROWEB data. Missing water levels are then interpolated using this relationship with known lake area values as input.

2.2.3. LWSC Estimation

Lake water storage cannot be measured directly and must be estimated using remote sensing data and in situ observations. Both lake area and water level information are required to establish a water level–storage relationship model.

LWSC refers to the temporal variation in lake water storage relative to a reference state. It reflects the combined effects of lake area change and water level variation. LWSC is widely used to quantify lake expansion and shrinkage over time. It is mainly controlled by changes in lake surface area and water level. Lake area increases when water level rises and decreases when water level drops.

Many previous studies estimate LWSC using the area–water level method [42,43]. In this study, the lake area is derived from Landsat imagery, and lake water level data are obtained from the HYDROWEB dataset. A linear relationship between lake area and water level is established to reconstruct a complete time-series for 1988–2025. LWSC is then calculated from the reconstructed data using the method proposed by Taube [44] (Equation (5)). For lakes with irregular shapes, lake volume is approximated using a frustum model:

$$\Delta V = \frac{1}{3}(L_{i+1} - L_i) \times (S_i + S_{i+1} + \sqrt{S_i \times S_{i+1}}) \quad (5)$$

where ΔV is the change in lake water storage when the lake water level changes from L_i to L_{i+1} ; S_i and S_{i+1} are the lake surface areas at time i and $i + 1$, respectively. The long-term time series of LWSC is obtained by accumulating the incremental storage changes step by step.

2.2.4. Trend Analysis of Lake Water Storage and Meteorological Factors

The Mann–Kendall (MK) trend test [45,46] is a nonparametric statistical method widely used for detecting monotonic trends in time-series. It evaluates whether the observed variations over time result from natural fluctuations or from a significant long-term trend by comparing the relative magnitude of sequential data values. This method does not require the data to follow a specific distribution and is robust to outliers and missing values. Due to its wide applicability and simple computation, the MK test is commonly applied to the trend analysis of temperature, precipitation, and hydrological variables under climate change conditions.

However, when a time-series exhibits serial autocorrelation, the conventional MK test tends to overestimate the statistical significance, thereby increasing the risk of Type I error. To address this limitation, Yue et al. proposed the Trend-Free Pre-Whitening Mann–Kendall (TFPW-MK) method as an improved variant of the standard MK test [47]. The core idea of the TFPW-MK approach is to first remove the trend component from the original series and then apply pre-whitening to the detrended residuals to eliminate the effect of autocorrelation. Subsequently, the trend component is added back to the pre-whitened series, and the standard Mann–Kendall test is performed on the resulting series. This method effectively reduces the influence of autocorrelation on the test statistics while preserving the long-term trend information in the original time-series.

The specific steps of the TFPW-MK method are as follows. Let the original observed time-series be X_t ($t = 1, 2, \dots, n$).

Step 1: Estimating the trend slope. The Theil–Sen estimator is used to compute a robust slope β for the time-series:

$$\beta = \text{Median} \left(\frac{x_k - x_i}{k - i} \right) \quad (6)$$

where β represents the median of all pairwise slopes, providing a robust estimate of the overall trend rate of change. When $\beta > 0$, the series has an upward trend; when $\beta < 0$, a downward trend.

Step 2: Removing the trend component. The trend is subtracted from the original series to obtain the detrended residual series Y_t :

$$Y_t = X_t - \beta \cdot t \quad (7)$$

This step isolates the non-trend fluctuations so that autocorrelation in the residuals can be assessed independently of the trend signal.

Step 3: Estimating the lag-1 autocorrelation coefficient. The lag-1 autocorrelation coefficient ρ_1 of the detrended series Y_t is calculated as follows:

$$\rho_1 = \frac{\sum_{t=2}^n (Y_t - \bar{Y})(Y_{t-1} - \bar{Y})}{\sum_{t=1}^n (Y_t - \bar{Y})^2} \quad (8)$$

where $\bar{Y}$ is the mean of Y_t . A value of ρ_1 significantly different from zero indicates that successive observations are correlated, which would inflate the MK test statistic if left uncorrected.

Step 4: Pre-whitening the detrended series. Pre-whitening is applied to remove the autocorrelation structure:

$$Y'_t = \begin{cases} Y_t, & t = 1 \\ Y_t - \rho_1 Y_{t-1}, & t = 2, 3, \dots, n \end{cases} \quad (9)$$

This operation produces a residual series Y'_t that is approximately free of serial autocorrelation, ensuring that the subsequent MK test statistics reflect genuine trend signals rather than autocorrelation artifacts.

Step 5: Restoring the trend component. The previously estimated trend is added back to the pre-whitened series to obtain the final series Y''_t for testing:

$$Y''_t = Y'_t + \beta \cdot t \quad (10)$$

This step ensures that the trend information removed in Step 2 is reintroduced before hypothesis testing, so that the MK test can correctly identify the direction and significance of the original trend.

Step 6: Performing the standard MK test. The MK test statistic S is computed on Y''_t by summing the signs of all pairwise differences:

$$S = \sum_{i=1}^{n-1} \sum_{k=i+1}^n \text{sgn}(x_k - x_i) \quad (11)$$

where a positive S indicates that later values tend to be larger than earlier ones (upward trend), while a negative S indicates the opposite.

$$\text{sgn}(\theta) = \begin{cases} 1, & \theta > 0 \\ 0, & \theta = 0 \\ -1, & \theta < 0 \end{cases} \quad (12)$$

where the sign function $\text{sgn}(\theta)$ takes the value 1, 0, or -1 depending on whether θ is positive, zero, or negative, respectively.

The variance of S under the null hypothesis of no trend is as follows:

$$\text{var}(S) = \frac{n(n-1)(2n+5)}{18} \quad (13)$$

This variance formula assumes no tied values; it provides the basis for standardizing S into a normally distributed statistic.

The standardized test statistic Z is then computed as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{var}(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S-1}{\sqrt{\text{var}(S)}}, & S < 0 \end{cases} \quad (14)$$

Z follows a normal distribution. $Z > 0$ indicates an upward trend, while $Z < 0$ indicates a downward trend. For a given significance level α , if $|Z| \geq Z_{1-\alpha/2}$, the time-series exhibits a statistically significant upward or downward trend.

To quantify the relationship between LWSC and meteorological factors, the Pearson correlation coefficient (r) was calculated using Equation (15). A hypothesis test was then conducted at a given significance level (p). When p indicated statistical significance, the correlation was considered significant and the null hypothesis of no linear correlation was rejected. Otherwise, the null hypothesis was not rejected.

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (15)$$

where $r \in [-1, 1]$. A value of r close to 1 or -1 indicates a strong positive or negative linear correlation, respectively; a value of r close to 0 indicates no linear correlation. X_i and Y_i represent the lake storage and meteorological factor data at time point i , respectively; $\bar{X}$ and $\bar{Y}$ are the corresponding means; and n is the length of the time-series.

2.2.5. Relationship Between LWSC and Climatic Factors

To quantitatively assess the driving effects of climatic factors on LWSC, this study employed trend removal analysis, partial correlation analysis, lag correlation analysis, and multiple linear regression.

First, linear detrending was applied to LWSC and the three climatic variables. For each time-series x_t , a linear regression against year t was fitted as follows:

$$x_t = a \cdot t + b + \epsilon_t \quad (16)$$

where a is the trend slope, b is the intercept, and ϵ_t is the residual.

The detrended series was then calculated as follows:

$$x_{\text{detrend},t} = x_t - (a \cdot t + b) \quad (17)$$

The subsequent partial correlation, lag correlation, and multiple regression analyses were all performed on the detrended series to avoid spurious correlations arising from shared long-term trends among variables.

Second, to isolate the net relationship between a given climatic factor and LWSC after removing the linear influence of the other two climatic factors, second-order partial

correlation coefficients were calculated using the residual method. Taking precipitation as an example:

$$r_{xy,z_1z_2} = \frac{r_{xy,z_2} - r_{x,z_1z_2} \cdot r_{y,z_1z_2}}{\sqrt{1 - r_{xz_1,z_2}^2} \cdot \sqrt{1 - r_{yz_1,z_2}^2}} \quad (18)$$

where x denotes P_{detrend} ; y denotes $LWSC_{\text{detrend}}$; and z_1 and z_2 stand for T_{detrend} and E_{detrend} , respectively.

3. Results

3.1. Analysis of Lake Changes

We applied the method described in Section 2.1 to extract the spring shoreline of Siling Co from 1988 to 2025 (Figure 3). Using these shorelines, we derived the time-series of lake area. To validate the extracted lake area and water level results, we selected only years with both observed water level and lake area data available. Linear regression, Huber regression, and RANSAC regression were used to analyze the correlation between altimetry-derived water level and lake surface area.

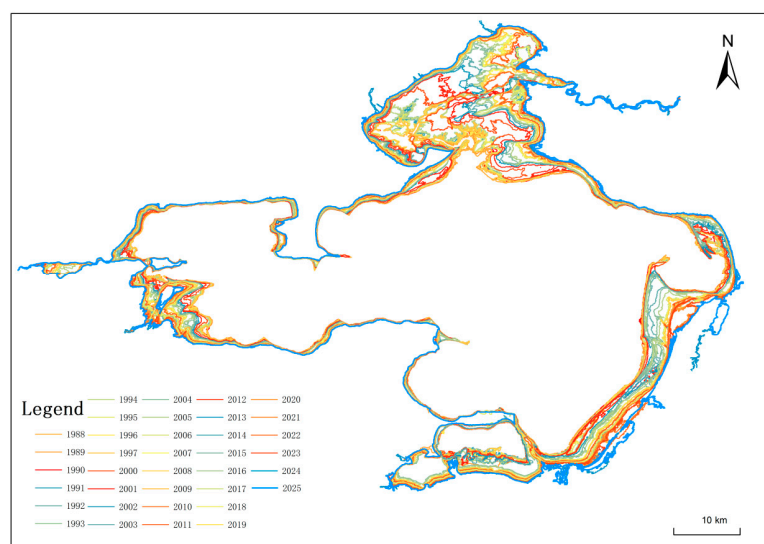


Figure 3. Trends in the shorelines of Lake Siling Co from 1988 to 2025.

As shown in Figure 4, the results of linear regression and RANSAC regression overlap completely. They produce identical R^2 , MAE, and RMSE values, indicating that the influence of outliers is limited. Linear regression shows a slightly higher R^2 and lower RMSE than Huber regression. Therefore, linear regression was selected to construct the area–water level relationship. The water level and surface area of Siling Co show a strong positive correlation ($R^2 = 0.977$), indicating excellent model fit. This area–water level relationship was used to reconstruct water levels for periods lacking direct measurements. It allowed the construction of long-term time-series datasets of lake area and water level from 1988 to 2025 (Figure 5).

Siling Co showed clear expansion from 1988 to 2025. The lake area increased from 1737.20 km² to 2543.03 km², representing a total increase of 805.83 km². During the same period, the water level rose by 14.33 m. Since 2003, Siling Co has connected with Yagen Co and gradually expanded toward the southwest. Note that due to missing remote sensing data in 1998 and 1999, effective lake boundaries could not be extracted for these years.

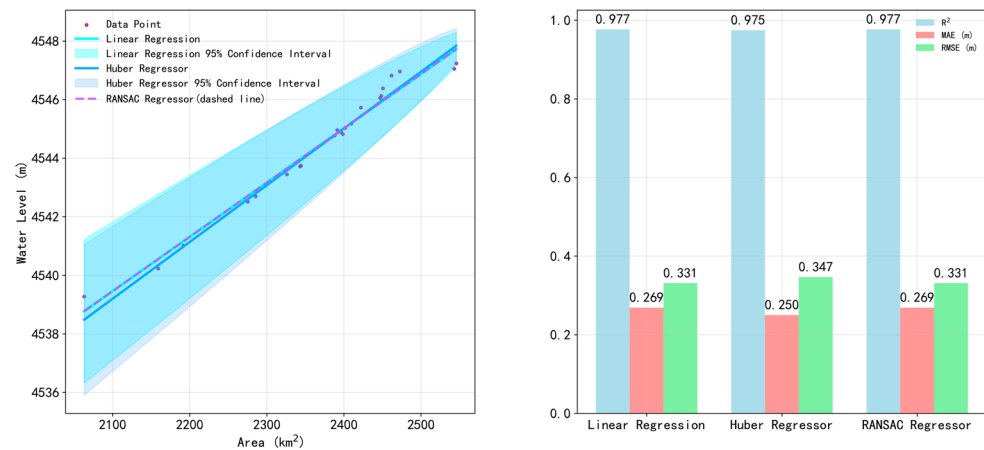


Figure 4. Relationship between water level and lake surface area; data point refers to lake area and water level data for the same year.



Figure 5. Results of constructing the time-series for the area and water level of Siling Co from 1988 to 2025.

As shown in the time-series of lake area and water level (Figure 5), the changes in Siling Co between 1988 and 2025 can be divided into three distinct stages.

1. The slow growth period (1988–1997): During this stage, the lake area fluctuated, first increasing and then decreasing. The overall area change rate was approximately 1.24%. Lake expansion was slow and relatively minor. The interpolated water level showed a similar trend to the lake area;
2. The rapid growth period (2000–2015): The lake area increased substantially, from 1758.70 km² in 1997 to 2421.95 km² in 2015. The total area change rate was 37.71%. Correspondingly, the water level rose from 4533.13 m to 4545.73 m, a total increase of 12.60 m. The mean annual increase in lake area was 28.26 km²/a, and the mean annual rise in water level was 0.52 m/a. This stage exhibited the fastest growth rates for both lake area and water level;
3. The growth period (2015–2025): Both lake area and water level decreased synchronously from 2015 to 2017 before resuming growth after 2017, with change rates of −1.40% and 6.49%, respectively. Overall, both variables exhibited an increasing trend. The total area growth rate was approximately 5.0%, and the water level rose by 1.33 m and increased at a much slower rate than in the previous stage. During 2019–2025, the mean annual increase in lake area was 7.91 km²/a, and the mean annual rise in water level was 0.30 m/a.

Based on the area–water level relationship constructed in this study, we obtained complete long-term time-series of water level and lake area (Figure 5). LWSC were calculated using Equation (5), and the results are shown in Figure 6. The figure clearly illustrates both interannual and cumulative changes in water storage. From 1988 to 2025, total water storage of Siling Co increased by 30.42 km^3 , accompanied by a continuous rise in water level. In 2003, the water level reached the watershed between adjacent lakes. Siling Co merged with Yagen Co through hydrological reorganization. It expanded southwestward, inundating pasture grasslands in the nearby low-elevation lakeshore zone.

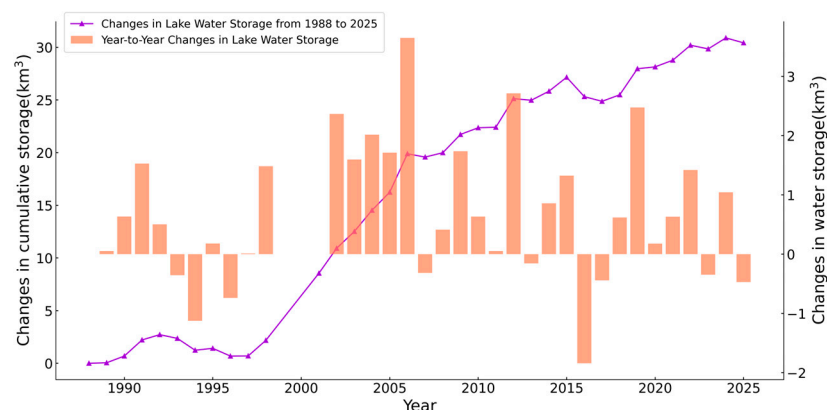


Figure 6. Cumulative water storage changes in Siling Co from 1988 to 2025 and interannual water storage changes between adjacent years.

3.2. Relationship Between LWSC and TWS Anomalies

Lake dynamics play an important role in TWS anomalies. To investigate the relationship between LWSC of Siling Co and TWS anomalies from 2002 to 2024, LWSC was compared with seasonal TWS anomalies in spring, summer, autumn, and winter (Figure 7). The mean TWS anomalies were 0.627 cm from April 2002 to February 2015 and increased to 4.737 cm from March 2015 to February 2025.

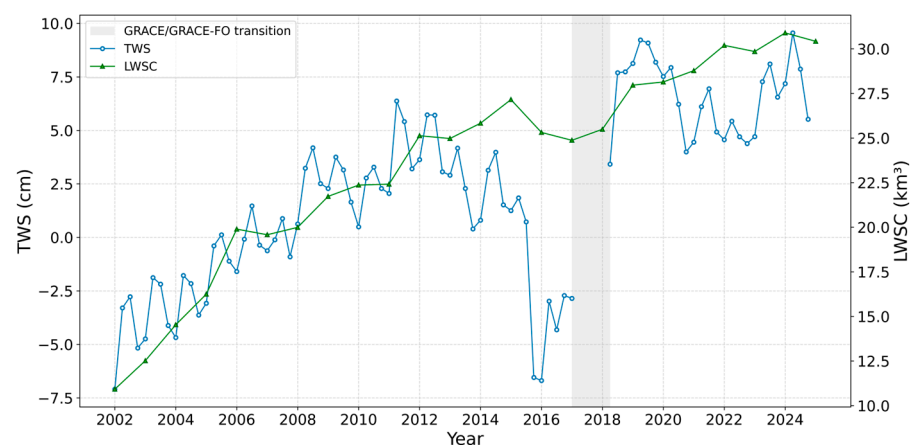


Figure 7. Temporal trends in cumulative LWSC and TWS anomalies of Siling Co from 2002 to 2025.

From 2002 to 2013, LWSC and TWS exhibited similar temporal trends. From 2013 to 2019, their variations were broadly consistent but not fully synchronized, indicating a lagged response of TWS to LWSC. Previous studies reported a pronounced global decline in TWS during May 2014–March 2016, mainly associated with consecutive El Niño events [48]. After 2019, TWS anomalies showed a clear decreasing trend, whereas LWSC continued to increase slowly, revealing a divergence between LWSC and TWS anomalies.

Pearson correlation coefficients (r) between TWS anomalies and LWSC were calculated for different time periods and lag years. Statistical significance is indicated using an asterisk (*). The lag analysis results are shown in Figure 8. For the entire period from 2002 to 2024, as well as for the subperiod 2013–2019, the highest correlation and significance occur when TWS lags LWSC by one year ($r = 0.79$). During 2002–2013, the strongest correlations are observed when TWS lags LWSC by one year and by four years ($r = 0.98$).

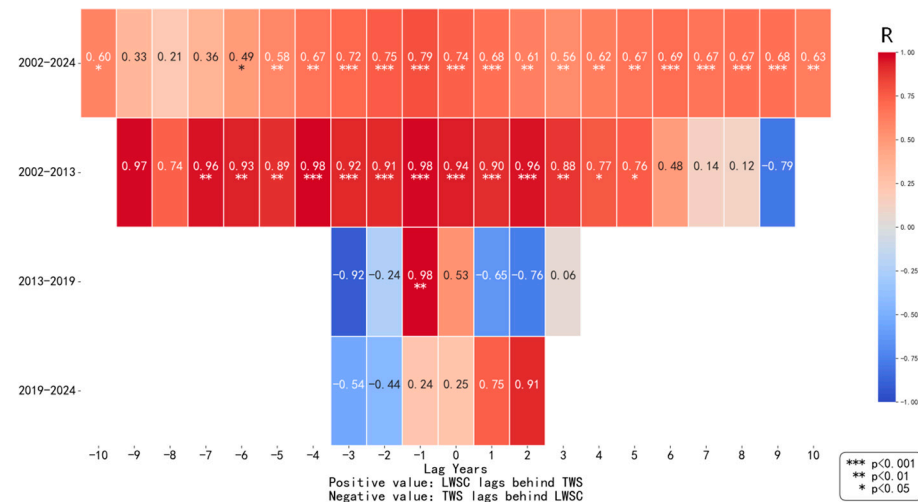


Figure 8. Lead-lag analysis between TWS anomalies and LWSC. Positive values on the x-axis indicate that LWSC lags behind TWS, whereas negative values indicate that TWS lags behind LWSC.

LWSC is one component of TWS. The lag of TWS behind LWSC has a physical explanation: other TWS components, such as soil water and groundwater, respond more slowly to climate forcing than lake water does. Previous studies have shown that soil moisture and groundwater on the TP typically respond to climate signals within several months to one year [49–51]. Therefore, the major TWS components generally complete their hydrological response within one year. Furthermore, existing studies have shown that the response lag of TWS to precipitation and other climate signals on the TP is typically within 1–3 months [52–54]. A four-year lag between TWS and LWSC would imply that one or more terrestrial water components require approximately four years to respond to climate forcing. This timescale exceeds the known response times of TWS components on the TP. It also lacks a clear physical basis. Therefore, the four-year lag was excluded. In contrast, a one-year lag is consistent with the typical response timescales of soil moisture and groundwater and is, therefore, physically plausible. During 2019–2024, the strongest correlation occurs when TWS leads LWSC by two years. However, this relationship is not statistically significant ($p \geq 0.05$), indicating that the null hypothesis of no correlation cannot be rejected. Overall, for the period 2002–2019, the strongest and most statistically significant relationship is observed when TWS lags LWSC by one year. The observed one-year lag between LWSC and TWS anomalies may reflect the time required for precipitation signals to propagate through the hydrological system. This lag includes temporary storage in soil moisture, groundwater, and permafrost. However, because TWS anomalies integrate changes in multiple water storage components, the relative contribution of each component cannot be distinguished from the present analysis.

4. Discussion

4.1. Analysis of Climate Factors and LWSC

Climate impacts on lake water storage are controlled by several factors, including precipitation, glacier meltwater, air temperature, and potential evaporation. A rising air

temperature enhances evaporation from the lake surface. Increasing precipitation provides direct water input and increases lake inflow through runoff, which promotes lake expansion. Accordingly, this study focuses on air temperature, precipitation, and evaporation as the key climate variables. Due to large gaps in precipitation records at some meteorological stations during certain years, annual mean air temperature, mean daily precipitation, and annual evaporation were used. These variables were used to calculate Pearson correlation coefficients (r) with LWSC.

From 1988 to 2022, both the annual mean air temperature and mean daily precipitation recorded at meteorological stations surrounding Siling Co exhibited extremely significant increasing trends ($p < 0.01$). The annual mean air temperature increased at a rate of $0.35\text{ }^{\circ}\text{C}/10\text{a}$. The mean daily precipitation increased at a rate of $0.59\text{ mm}/10\text{a}$. The multi-year mean air temperature was $0.80\text{ }^{\circ}\text{C}$, varying from a minimum of $-0.66\text{ }^{\circ}\text{C}$ in 1997 to a maximum of $2.21\text{ }^{\circ}\text{C}$ in 2022. The multi-year mean daily precipitation was 1.79 mm , with values ranging from 0.78 mm in 1999 to 3.74 mm in 2016.

According to the detrended result of $\rho_1 = 0.3762$, the multi-year mean daily precipitation exhibits a moderate positive autocorrelation. From 1988 to 2024, annual evaporation also showed a significant increasing trend ($p < 0.01$), with a rate of $11.5\text{ mm}/10\text{a}$. The multi-year mean annual evaporation was 607.03 mm , ranging from 552.07 mm in 1997 to 654.59 mm in 2024; details can be found in Table 2 and Figure 9.

Table 2. Results of TFPW-MK trend test for key climatic and hydrological variables.

Variable	ρ_1	S	Z	p -Value	Kendall's τ	Sen's Slope
Annual mean air temperature	-0.2104	253	3.579	0.0003	0.4252	$0.0348\text{ }^{\circ}\text{C}/\text{a}$
Mean daily precipitation	0.3762	249	3.522	0.0004	0.4185	$0.0591\text{ mm}/\text{a}$
Annual evaporation	-0.0118	208	2.707	0.0068	0.3123	$1.1529\text{ mm}/\text{a}$

ρ_1 denotes the lag-1 autocorrelation coefficient used in the TFPW procedure; S is the Mann–Kendall test statistic; Z is the standardized test statistic; p -value indicates the significance level of the detected trend; Kendall's τ is the rank correlation coefficient indicating the strength and direction of the trend; and Sen's Slope represents the magnitude of the trend.

We used the Pearson correlation coefficient (r) to quantify the linear relationships between LWSC and key climatic factors (Figure 10). The results show that LWSC has moderate to strong positive correlations with annual mean air temperature ($r = 0.65$, $p < 0.001$) and mean daily precipitation ($r = 0.63$, $p < 0.001$). LWSC also has a significant positive correlation with annual evaporation ($r = 0.48$, $p < 0.01$).

We controlled for the linear effects of the other two climate factors. We then calculated the partial correlation coefficients between each climate factor and LWSC. The mean daily precipitation showed $r = 0.307$ ($p = 0.0826$), mean air temperature showed $r = 0.185$ ($p = 0.3021$), and annual evaporation showed $r = 0.058$ ($p = 0.7506$). None of these three coefficients reached significance at the $\alpha = 0.05$ level. However, the partial correlation for precipitation was clearly higher than those for temperature and evaporation.

These results suggest something important; after removing the long-term trend and excluding the influence of other climate factors, precipitation remains the main climatic driver of LWSC. At the interannual scale, precipitation made the largest net contribution to LWSC mean air temperature fluctuations. Temperature's net effect was weaker. Evaporation's net effect was extremely weak and can be considered negligible.

Overall, precipitation shows a relatively stronger association with LWSC in Siling Co than the other climatic factors. Mean air temperature and evaporation are also related to LWSC. However, the partial correlation analysis indicates that no single climatic factor has a statistically significant independent effect after controlling for the others. The combined effects of these three factors contribute to lake expansion.

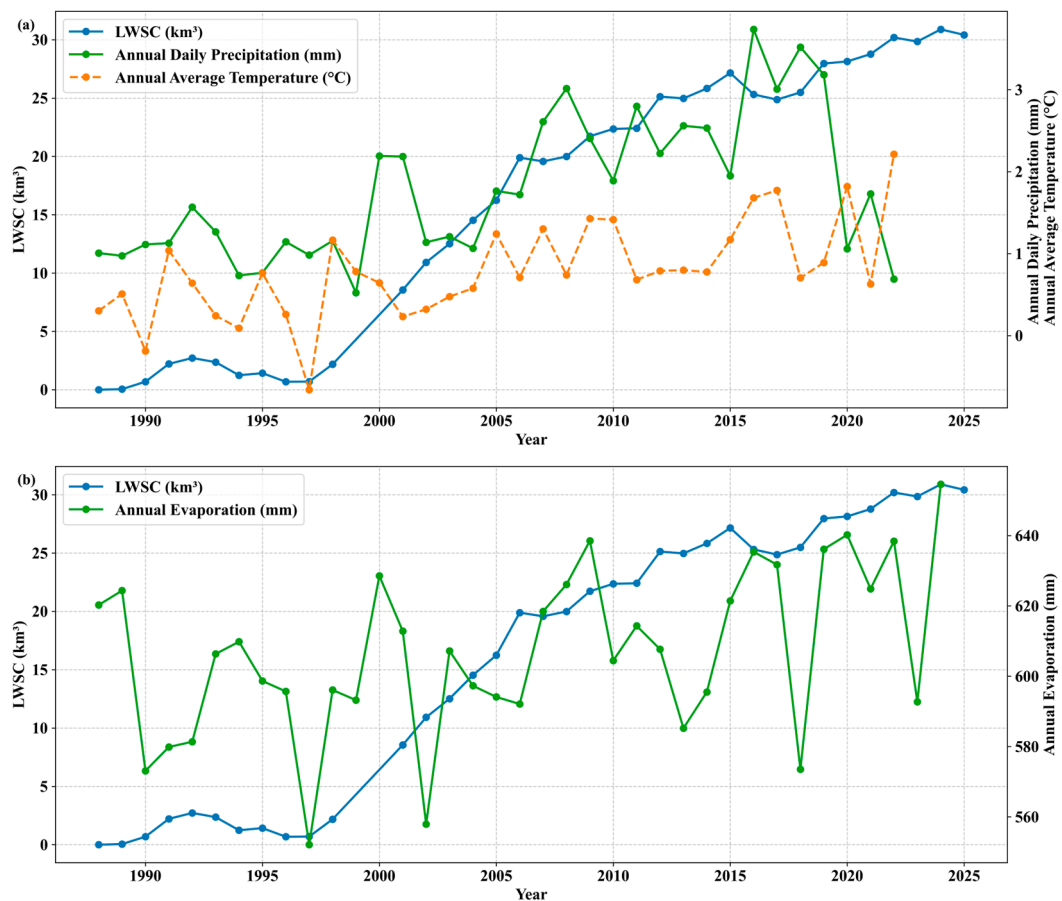


Figure 9. Trends in LWSC alongside key climatic variables. (a) Temporal variations in LWSC, annual daily precipitation and annual mean air temperature; (b) temporal variations in LWSC and annual evaporation.

The TP, known as the “Asian Water Tower”, plays a critical role in regional water resources and ecological security. According to the law of mass conservation, changes in lake water storage equal the difference between water input and output. Lake stability, therefore, depends on maintaining a hydrological balance: when inputs and outputs are equal, lake water level and surface area remain stable.

Global warming has accelerated glacier melting across the TP. In the short-term, this increases meltwater input to glacial lakes while simultaneously raising the risk of glacial lake outburst floods (GLOFs) [55]. Strong climate warming has already altered the regional water balance, resulting in a rapid lake level rise and lake area expansion [56]. As a glacial lake, Siling Co faces potential GLOF hazards, emphasizing the need for continuous monitoring and proactive risk management.

From 2019 to 2025, regional TWS exhibited a stable to slightly decreasing trend (Figure 7), with a mean annual change rate of -1.25 cm/a based on linear regression. Despite this regional decline, the water level and area of Siling Co continued to increase at mean annual rates of 0.30 m/a and 7.91 km²/a, respectively. However, these growth rates are much lower than those observed during 1997–2015, when the mean annual lake area expansion reached 28.26 km²/a. This pronounced slowdown indicates that the long-term rapid expansion of Siling Co is unlikely to continue.

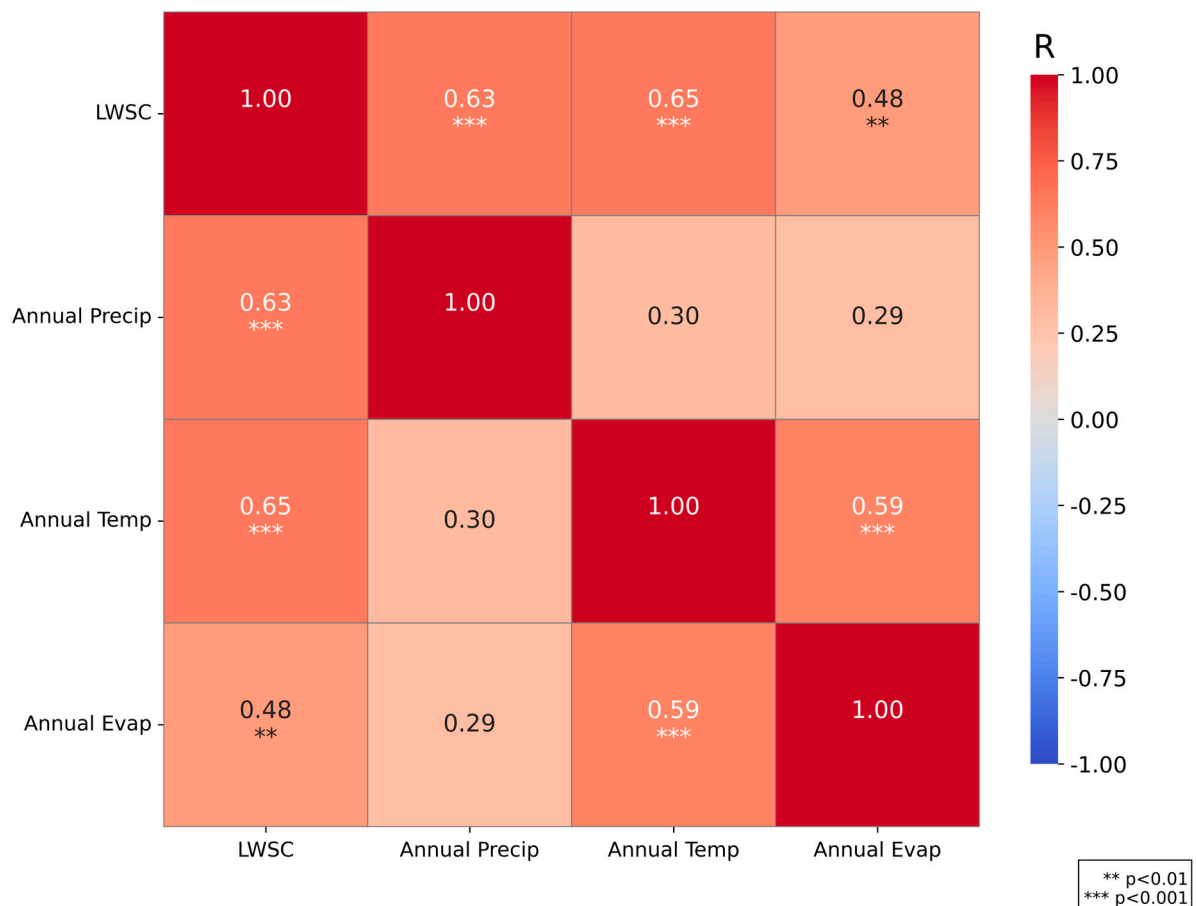


Figure 10. Pearson correlation matrix heatmap of LWSC and meteorological factors for Siling Co, asterisks indicate significance levels: ** $p < 0.01$, *** $p < 0.001$.

Based on the dynamic monitoring data of the spring shoreline of Siling Co from 1988 to 2025 shown in Figure 3, this study reveals the spatial distribution pattern of lake expansion of Siling Co. The relevant findings can provide a scientific basis for the implementation of major national projects, infrastructure construction, and road traffic safety. The long-term expansion trend of the lake, the overflow event of Siling Co in 2023 that led to the destruction of provincial highway S208, and the projected merger of Siling Co and Bange Co around 2030 can provide a reference for the site selection and layout of related projects on the TP. These events help to avoid situating facilities in areas that may be submerged in the future. The quantitative results of shoreline expansion direction and rate can further support highway route selection along the lake, the design of flood control facilities, and the laying of pipelines. These results help reduce the risk of infrastructure damage from the outset. The 2023 overflow event also highlights the direct threat that lake expansion poses to road traffic. The monitoring data and trend predictions from this study can help relevant departments identify high-risk road sections and establish early warning mechanisms. This can reduce road interruptions and traffic accidents caused by sudden lake expansion.

4.2. Study Limitations

4.2.1. Limitations of the GEE-Based Lake Area Estimation Method

This study developed a script on the GEE cloud computing platform to automatically extract lake area and shoreline for Siling Co, achieving satisfactory results. However, two limitations should be noted when applying this method to other lakes.

First, there are constraints related to computational resources and spatial scale. The GEE platform imposes limits on memory usage and processing extent for individual tasks.

The proposed method performs well for moderate-sized plateau lakes and has yielded reliable results for lakes such as Hala Lake. However, for significantly larger lakes, such as Qinghai Lake, the required processing extent exceeds the computational limits of a single GEE task, preventing successful completion. Siling Co's lake area currently falls within the method's reliable range. Although it is approaching the threshold, it is still within this threshold. However, its continued rapid expansion means that future monitoring efforts may eventually approach or exceed this computational limit. This should be considered when extending the time-series further.

This method has certain limitations related to computational resources and processing scale. Two steps create the main bottlenecks. The first is the global histogram calculation used in the Otsu thresholding algorithm. This step must process every image pixel across the entire study area. The second is the conversion of the water mask raster to vector format ("reduceToVectors"), along with the connected-component analysis ("reduceConnectedComponents"). Both of these are global operations. Unlike standard band calculations, GEE cannot easily split them into smaller parallel tile tasks. As a result, the computational load grows nonlinearly with two factors: the total number of pixels within the geometry boundary, and the complexity of the shoreline shape. When the processing load becomes too large, it can exceed the memory or time limits of a single GEE task.

This method has already been applied successfully to medium-sized lakes such as Hala Lake, producing reliable results. However, it failed for Qinghai Lake, which covers approximately 4000 km². The shoreline and area extraction could not be completed, due to the heavy computational load from the global operators described above. Siling Co currently falls within the reliable range of this method. However, the lake continues to expand, and its shoreline shape may become more complex over time. As the monitoring time-series extends further, the processing load may gradually approach this computational limit.

Second, the method has limited capability in identifying water bodies under snow- and ice-covered conditions. For lakes near glaciers or in regions with extensive snow and ice cover, extraction accuracy decreases substantially. Although the MNDWI can effectively distinguish water from land under normal conditions, the spectral signatures of glaciers, snow, and lake water become highly similar in complex snow- and ice-rich environments. In such cases, the Otsu automatic thresholding algorithm fails to effectively separate these surface types, often resulting in the misclassification of snow- and ice-covered areas as water bodies. Consequently, lake area may be systematically overestimated, and shoreline extraction accuracy can be significantly reduced.

In summary, the current method is most suitable for moderate-sized inland lakes on the central TP that experience limited snow and ice interference in their surrounding areas. However, as Siling Co continues to expand, its lake area may eventually exceed the upper limit that the code used in this study can process. This represents a limitation of the current code.

4.2.2. Indirect Estimation of Lake Water Storage

This study estimated water storage changes in Siling Co indirectly by combining lake area and water level observations. The study assumed assuming a linear relationship between lake area and water level. These two aspects represent the primary sources of uncertainty in the water storage estimation.

Regarding the indirect estimation approach, the method can only capture relative trends in water storage and cannot provide the absolute lake water volume. This limitation stems primarily from the lack of systematic bathymetric and lake basin topographic data for Siling Co. Without high-precision bathymetric surveys, the three-dimensional morphology

of the lake basin cannot be accurately characterized. This results in considerable uncertainty in absolute water storage estimates.

With respect to the linear relationship assumption, this simplification is reasonably applicable to flat and open inland plateau lakes. When water level fluctuations remain within a limited range, the lake basin morphology is relatively regular. This allows the area–water level relationship to be approximated as linear over short intervals [7]. However, from a strict hydrological and geomorphological perspective, the actual relationship between lake area and water level is typically nonlinear. The relationship depends on the three-dimensional basin topography, shoreline geometry, and hydrological processes.

Specifically, when the water level rises across different topographic steps, the area increment per unit change in water level may vary abruptly. During the rapid expansion of Siling Co in recent years, the lake has repeatedly inundated surrounding shallow shoals and merged with adjacent small lakes, such as Yagen Co. These discontinuous shoreline changes introduce noticeable nonlinear characteristics into the area–water level relationship during certain periods. Consequently, the linear assumption may introduce systematic bias in those stages.

Although the long-term relative variation trends analyzed in this study are less sensitive to these limitations, the combined effects of these uncertainties still warrant careful consideration. Future studies should prioritize bathymetric surveys of Siling Co to establish an accurate area–elevation–volume relationship (hypsometric curve). This would replace the current linear approximation. It would enable more precise estimation of absolute water storage. This would improve the accuracy and reliability of lake water storage reconstructions.

4.2.3. Ice Surface Interference in Satellite Altitude Measurement Data

The HYDROWEB satellite altimetry product generally employs retracking algorithms designed for open water surfaces. It uses these algorithms when generating water surface elevation (WSE) data. The product does not specifically correct for frozen lake surface conditions. In this study, the mean WSE from March to May was used to represent the annual low-water-level condition. However, previous studies have reported the following lake ice phenology for Siling Co [57]. The lake typically begins to freeze from late November to early December. It becomes fully ice-covered between late December and early January. It usually starts melting from late March to early April. This is followed by an approximately two-week transition period with coexisting ice and open water, with the lake becoming completely ice-free by late April.

Consequently, during the entire month of March and the first half of April, the lake surface of Siling Co remains either fully frozen or in a mixed ice–water state. During this period, satellite altimetry signals are reflected from the ice or snow surface rather than the open water surface. This differs fundamentally from the retracking conditions assumed for open water and may introduce systematic elevation bias.

It should be noted that, although ice-surface interference may affect observations in March and early April, data from late April to May correspond to completely ice-free open water conditions. These ice-free observations constitute the dominant proportion of the March–May mean and thus partially mitigate the influence of ice-affected data on the averaged water level. Moreover, since this study primarily focuses on long-term trends in lake water level rather than absolute elevation values, the relative stability of systematic bias across years supports the reliability of the trend analysis.

Nevertheless, this remains an inherent uncertainty of the present study. Future altimetry studies on seasonally frozen lakes should incorporate lake ice phenology data. This data can help systematically identify and exclude ice-period observations. They can also apply

specialized retracking algorithms designed for ice and snow surfaces. These measures will further improve data quality and result reliability.

4.2.4. Limitations of Using a Single GRACE Mascon Product

It should also be noted that comparing TWS anomalies with LWSC involves a degree of conceptual inconsistency. TWS anomalies represent an integrated hydrological signal. This signal encompasses multiple water storage components. These components include groundwater, soil moisture, snow, canopy water, river storage, and lake storage. LWSC, in contrast, reflects only the lake storage component within this integrated signal. As a result, the relationship between TWS anomalies and LWSC examined in this study does not fully isolate the lake-specific contribution from the other covarying hydrological components. Part of the observed covariation may be attributable to changes in groundwater, soil moisture, or snow storage rather than to the lake itself.

In addition, this study relied exclusively on the JPL RL06.3 mascon solution to characterize TWS anomalies over the Siling Co Lake. GRACE/GRACE-FO TWS anomalies estimates are known to vary among processing centers (e.g., CSR, JPL, GSFC), owing to differences in mascon design, spatial filtering, leakage correction, and scaling factor approaches. Although mascon solutions generally show better agreement with one another than spherical harmonic solutions, non-negligible discrepancies in both the magnitude and the temporal pattern of TWS anomalies can still arise. These discrepancies are particularly obvious over relatively small and topographically complex basins such as those on the TP. Signal leakage and limited spatial resolution amplify inter-product uncertainty in these areas. By relying solely on the JPL product, this study cannot fully rule out the possibility that part of the reported relationship between TWS anomalies and LWSC reflects processing-center-specific characteristics. It may not reflect genuine hydrological signals.

Taken together, these two factors represent limitations of the current analysis. Future studies should attempt to decompose TWS anomalies into individual storage components. This can be performed by using auxiliary land surface model outputs to remove non-lake contributions. Future studies should also incorporate and intercompare multiple GRACE mascon products, such as CSR and GSFC, or adopt an ensemble-mean approach. These steps will more rigorously assess the robustness of TWS anomalies-based findings. They will also better quantify the methodological uncertainty associated with both signal decomposition and product selection.

4.3. Accuracy Assessment of Lake Area Extraction Results

To objectively evaluate the reliability of the Siling Co Lake area time-series extracted from Landsat imagery in this study, we compared our results with two reference datasets: (1) “The lakes larger than 1 km² in Tibetan Plateau (v3.1) (1970s–2022)” [58], and (2) the “Siling Co Changes Dataset in Half a Century (1972–2020)” [59]. The comparison results are shown in Figure 11 and Table 3.

The validation results from both reference datasets show that the water area extracted in this study has high accuracy and reliability. Table 3 presents detailed accuracy metrics. When comparing our extracted lake area with the datasets 1 and 2, the R² values exceed 0.98 in both cases. The MAPE values do not exceed 1% in either case. These results indicate strong agreement between our extracted data and the reference datasets over the long time-series. This confirms that the GEE-based code used in this study is effective and stable for monitoring water body dynamics in the Siling Co Lake.

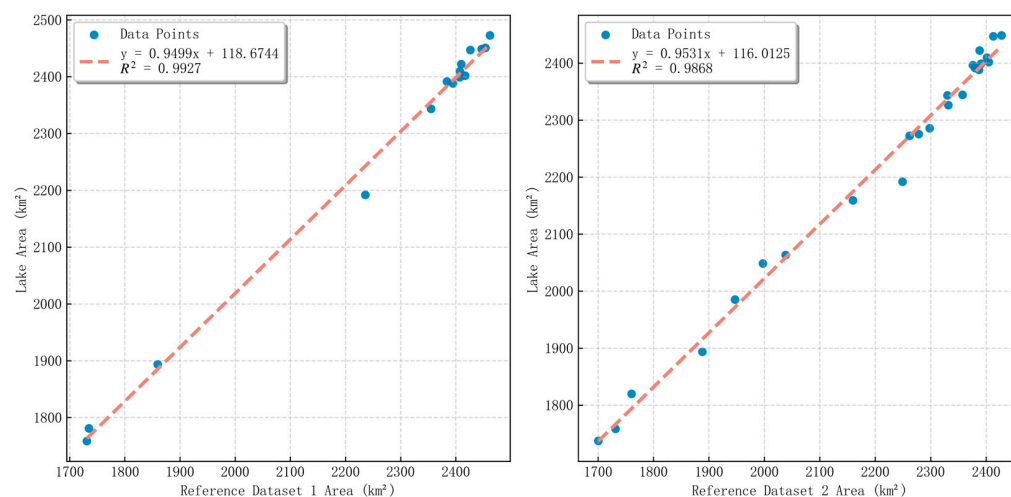


Figure 11. Lake area extraction accuracy assessment plot.

Table 3. Validation results of the Siling Co extraction area against reference datasets.

	Reference Datasets	R	R ²	RMSE (km ²)	MAE (km ²)	MAPE (%)
1	The lakes larger than 1 km ² in Tibetan Plateau (v3.1) (1970s–2022)	0.9976	0.9927	21.8551	16.6778	0.81%
2	Siling Co Changes Dataset in Half a Century (1972–2020)	0.9955	0.9868	27.0029	20.6680	1.00%

5. Conclusions

Based on multi-source remote sensing data combined with meteorological factors, we analyzed water storage changes in Siling Co over the past 38 years. The main conclusions are as follows:

(1) From 1988 to 2025, the lake area, water level, and water storage of Siling Co on the TP showed an overall increasing trend. The lake area increased from 1737.20 km² to 2543.03 km², an increase of 805.83 km². The water level rose by 14.33 m, and water storage increased by 30.42 km³;

(2) The climate attribution analysis shows that LWSC in Siling Co is significantly correlated with annual mean air temperature ($r = 0.65$, $p < 0.001$), mean daily precipitation ($r = 0.63$, $p < 0.001$), and annual evaporation ($r = 0.48$, $p < 0.01$). However, partial correlation analysis reveals that none of these factors retains a statistically significant independent effect once the influence of the others is removed. Precipitation shows the relatively highest partial correlation ($r = 0.307$). This suggests that it may play a relatively more important role. These results indicate that the water storage changes in Siling Co arise from the combined effects of multiple climatic factors together with non-climatic processes. The changes are not driven by a single dominant climatic factor;

(3) Spatially, the lake expanded in all directions, with particularly pronounced growth along the north–south axis. This expansion may pose a threat to Provincial Road S506 and National Highway G317. Comparison with GRACE/GRACE-FO data shows that TWS lagged behind LWSC by approximately one year during 2002–2024. This suggests a delayed TWS response to LWSCs in Siling Co.

Against the background of global warming, the continued expansion of Siling Co may increase the risk of lake outburst events. It may also threaten regional ecosystems and road safety. Although the lake expansion rate has slowed in recent years, strengthened real-time monitoring and early warning systems are still recommended. These measures can provide scientific support for preventing risks to roads, villages, and other infrastructure.

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Data Availability Statement: The Google Earth Engine (GEE) code script used for lake area extraction in this study is publicly available at <https://code.earthengine.google.com/86faef4107a5aba84980495dbb0672d1> (accessed on 10 July 2026). Satellite altimetry-derived lake water level data were obtained from <https://www.theia-land.fr/en/hydroweb/> (accessed on 10 July 2026). Monthly precipitation and air temperature data were obtained from ground-based meteorological station observations provided by the National Centers for Environmental Information (NCEI), National Oceanic and Atmospheric Administration (NOAA), and are available at <https://www.ncei.noaa.gov/access/search/datasets/global-summary-of-the-month/> (accessed on 10 July 2026). GRACE and GRACE-FO mascon solutions were obtained from <https://podaac.jpl.nasa.gov/GRACE?tab=mission-objectives§ions=about+data> (accessed on 15/7/2026). The reference datasets used for validation in this study are publicly available. The “Lakes Larger than 1 km² on the Tibetan Plateau (v3.1) (1970s–2022)” dataset can be accessed at the National Tibetan Plateau/Third Pole Environment Data Center (TPDC): <https://www.tpdc.ac.cn/home> (accessed on 10 July 2026). The “Siling Co Changes Dataset in Half a Century (1972–2020)” can be accessed via the Global Change Research Data Publishing and Repository: <https://www.geodoi.ac.cn/doi.aspx?Id=1691> (accessed on 10 July 2026). The lake area, water level, and lake water storage changes (LWSC) time-series derived in this study are available from the corresponding author upon reasonable request.

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