



Article Long-Term 10 m Resolution Water Dynamics of Qinghai Lake and the Driving Factors

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Abstract: As the largest inland saltwater lake in China, Qinghai Lake plays an important role in regional sustainable development and ecological environment protection. In this study, we adopted a spatial downscaling model for mapping lake water at 10 m resolution through integrating Sentinel-2 and Landsat data, which was applied to map the water extent of Qinghai Lake from 1991 to 2020. This was further combined with the Hydroweb water level dataset to establish an area-level relationship to acquire the 30-year water level and water volume. Then, the driving factors of its water dynamics were analyzed based on the grey system theory. It was found that the lake area, water level, and water volume decreased from 1991 to 2004, but then showed an increasing trend afterwards. The lake area ranges from 4199.23 to 4494.99 km². The water level decreased with a speed of ~0.05 m/a before 2004 and then increased with a speed of 0.22 m/a thereafter. Correspondingly, the water volume declined by 5.29 km³ in the first 13 years, and rapidly increased by 15.57 km³ thereafter. The correlation between climatic factors and the water volume of Qinghai Lake is significant. Precipitation has the greatest positive impact on the water volume variation with the relational grade of 0.912, while evaporation has a negative impact.

Keywords: water level; water volume; spatial downscaling; water dynamics; climate change

1. Introduction

Lakes are an important part of global hydrological and ecological processes [1–3], providing humans with indispensable resources and services, including drinking water supply, agricultural production, transportation, recreation, fishery, etc. [4,5]. Ongoing global warming and climatic change [6] is enhancing the global hydrological cycle and affecting water availability. As a result, efficient management of water resources is needed [7,8]. Warminginduced hydrological cycle intensification and its impacts on local and global ecosystems have brought increasing attention to the links between climatic change/variability, hydrological processes, and water resources across various temporal and spatial scales during the last few decades [9,10]. Therefore, understanding the hydrological changes of lakes and their potential driving factors can provide insights into lake conservation and water resource management [11,12]. As the largest inland saltwater lake in China, Qinghai Lake is located at the northeastern part of the Tibetan Plateau, which is extremely sensitive to climate change and plays a crucial role in maintaining the regional hydrological cycle [13]. Therefore, monitoring the long-term dynamics of Qinghai Lake and analyzing its driving factors are of great significance for local sustainable development and ecological environment protection.

Remote sensing provides an effective way of monitoring surface water, mainly in the forms of microwave remote sensing and optical remote sensing. Microwave remote sensing is powerful due to its less atmospheric effect and all-weather observation [14],



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). while optical remote sensing is widely used because of the data availability and appropriate spatial and temporal resolutions [15]. For example, high temporal resolution multispectral data, including MODIS and AVHRR, have been widely used to detect the seasonal and inter-annual changes of lakes in the Tibetan Plateau [16], bearing in mind that the coarse resolution may cause a lack of water extraction details and low accuracy at a regional scale [17,18], while higher spatial resolution remote sensing data (e.g., Landsat imagery) make it possible to accurately detect and delineate the water body information [19–22]. For example, Cui et al. [23] analyzed the coastline change of Qinghai Lake and its surrounding lakes from 1973 to 2015 by utilizing multitemporal Landsat imagery. Zhang et al. [24] estimated the water balances of the ten largest lakes in China using ICESat and Landsat data between 2003 and 2009. They proved that satellite remote sensing could serve as a fast and effective tool for estimating lake water balance. Although Landsat imagery has higher spatial resolution in comparison with MODIS or AVHRR, the accuracy of water body extraction was still limited by its 30 m resolution. Sentinel-2 satellites are able to obtain multispectral remote sensing data with a higher spatial resolution of up to 10 m, which is assumed to be better for mapping surface water [25]. Existing research, such as Du et al. [26] and Yang et al. [27], has demonstrated that Sentinel-2 data can provide more explicit and accurate surface water information with the advantages of intensively and continuously monitoring the surface of the Earth and higher spatial resolution. However, as this is a recent satellite mission, its data have a relatively short time series, which fails to meet the requirements of long-term analysis of lake water dynamics.

The mixed pixel issue usually hinders the accurate drawing and monitoring of lake water. There are two popular methods to alleviate mixed pixel issues, pixel unmixing and reconstruction, and spatial and temporal fusion [25]. The purpose of pixel unmixing and reconstruction is to achieve higher resolution land cover mapping from coarse-resolution data under the assumption that each mixed pixel can be expressed in the form of certain combinations of a number of pure spectral signatures [25]. Spatial and temporal fusion (spatio-temporal fusion) aims to blend high spatial resolution data with high temporal resolution data to achieve both high spatial and high temporal resolutions [28–31], so that the mixed pixel issue of the coarse spatial resolution data can be alleviated. Wu et al. [32] proposed a downscaling algorithm that established a statistical regression model between MODIS and Landsat data for generating a higher resolution inundation map from MODIS. Through this downscaling process, they managed to generate 30 m water maps from coarse resolution MODIS data while keeping their high temporal resolution. It was proved that the downscaled water maps provide more spatial details and have higher accuracy.

The rapid development of remote sensing technology also brings new ideas for monitoring lake water volume changes. This can be achieved by combing the lake area derived from optical remote sensing and water level estimated by satellite altimetry data. Satellite radar/laser altimeters such as TOPEX/POSEIDON, ENVISAT, JASON-1, and ICESat/GLAS have been successfully applied for monitoring lake level variations [33–36]. For example, Zhang et al. [37] utilized Landsat and ICESat datasets to examine annual changes in lake area, level, and volume of the Tibetan Plateau and explored the reasons for the lake water volume changes from the 1970s to 2015. The Hydroweb, maintained by LEGOS/GOHS in France, provides water level/area information derived from a combination of multiple altimetry satellite observations of more than 150 inland lakes and reservoirs [38], which serves as a useful data source for lake monitoring. For example, Liu et al. [39] combined the Hydroweb and Landsat data recorded from 1975 to 2015 to evaluate water volume variations and the water balance of Taihu Lake.

In this study, we aim to achieve a long-term and high-resolution analysis of the water variation of Qinghai Lake in the past 30 years. To fulfil this objective, we adopt Wu et al.'s [32] downscaling method to generate 10 m resolution water maps from a long-term Landsat image series, with Sentinel-2 data as the auxiliary. To facilitate the computation, we implement this method on Google Earth Engine (GEE) [40], an advanced remote sensing cloud computing platform for large-scale and long-term remote sensing

analysis and processing. We also want to combine the long-term water area variation with water level information to estimate the water volume dynamics of Qinghai Lake, and ultimately analyze the driving factors.

2. Study Area and Materials

2.1. Study Area

Qinghai Lake is the largest plateau inland saltwater lake in China, located in the northeast corner of the Tibet Plateau ($36^{\circ}32'-37^{\circ}15'$ N, $99^{\circ}36'-100^{\circ}47'$ E) (Figure 1) at an altitude of 3196 m. It belongs to the semi-arid climate on a continental plateau, with large evaporation, great temperature difference between day and night, and a short frost-free and long freezing period [41]. The annual precipitation in the lake area is about 357 mm, and the annual average temperature is approximately 1.2 °C [42]. More than 40 rivers (or streams) flow into Qinghai Lake, with the two largest rivers, the Buha River and Shaliu River, accounting for 63% of the total recharge volume [43]. As a closed inland lake, the variations of Qinghai Lake water are closely related to, and highly affected by the climate, while human activities contribute little [41,42,44], probably because it is a salt lake.



Figure 1. Qinghai Lake Basin.

2.2. Materials

Data used in this study include Landsat imagery, Sentinel-2 imagery, water level data from the Hydroweb, and meteorological data (Table 1). Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI data were employed together to implement a long-term earth observation from 1991–2020. Sentinel-2 MSI imagery, with a spatial resolution up to 10 m, was employed to establish the downscaling model to generate 10 m water extent from Landsat data. Both Landsat and Sentinel-2 data were obtained and pre-processed on GEE. Considering the interference of clouds, Landsat images from May to November were mosaiced to generate a cloud-free image for each year. In order to reduce distortion caused by projection, Sentinel-2 data were reprojected to the same coordinate system as Landsat data (WGS 84/UTM zone 47N). The Hydroweb dataset (http://Hydroweb.theia-land.fr, accessed on 20 October 2020) provides long-term water level, area, and water storage estimations of major lakes globally. Its water level dataset is a fusion of multiple altimetry satellites

with different service years, including Topex-Poseidon (1992–2005), Jason-1 (2001–2013), ICESat (2003–2009), Jason-2 (2008-), Jason-3 (2016-), Sentinel-3A (2016-), ICESat-2 (2018-), and so on [35]. Meteorological data were obtained from the China Surface Climate Data Daily Value Dataset (V3.0) published by the China Meteorological Data Service Center (https://data.cma.cn/en/?r=data/index, accessed on 20 October 2020). We acquired temperature, evaporation, and precipitation of Gangcha, Chaka, and Gonghe stations near Qinghai Lake from this dataset, and used them to analyze the driving factors of Qinghai Lake's water dynamics.

Table 1. Materials used in this study.

	Year	Selected Bands	Spatial Resolution (m)	Purpose
Landsat 5 TM	1991–2011	B2, B4	30	Water extraction
Landsat 7 ETM+	2012	B2, B4	30	Water extraction
Landsat 8 OLI	2013–2020	B3, B5	30	Downscaling Model & water extraction
Sentinel-2 MSI	2015-2019	B3, B8	10	Downscaling Model
Hydroweb dataset	1995-2020	-	-	Water volume estimation
Meteorological dataset	1991–2017	-	-	Driving factor analysis

3. Methodology

We utilized Landsat and Sentinel-2 images in the overlapping period (2015–2019) on GEE to establish the statistical regression downscaling model as developed by Wu et al. [32]. This model was then applied to generate long-term (1991–2020) and high-resolution (10 m) water maps from Landsat imagery. Through integrating with the water level from the Hydroweb dataset, the water volume variation in the past 30 years was analyzed based on the area-level relationship. Finally, the meteorological dataset was used to analyze the driving factors of lake volume changes. The flowchart of the methodology of this study is shown in Figure 2.



Figure 2. Workflow of this study.

3.1. Downscaled Mapping of Surface Water

We adopted the statistical regression model proposed by Wu et al. [32] to downscale Landsat imagery from 30 m to 10 m resolution, with the assistance of 10 m resolution Sentinel-2 data. This model is based on regressing water index images derived from Landsat and Sentinel-2 (Equation (1)). Specifically, Landsat 8 and Sentinel-2 with close dates (less than 3 days) from 2015 to 2019 were selected to construct the regression model (Table 2). Among the selected 11 pairs of Landsat-8 and Sentinel-2 images, the one on

23 October 2018 was selected to validate the downscaled results only, while the remaining were selected for regression.

$$NDWI_{i,i,t}^{Fine} = a_{i,j} \cdot NDWI_{i,i,t}^{Coarse} + b_{i,j},$$
(1)

Table 2. Selected Landsat 8 and Sentinel-2 imagery for establishing the regression model. The bolded pair was for validation only.

Sequence	The Date of Landsat 8	The Date of Sentinel-2
1	2016/07/29	2016/07/30
2	2016/10/17	2016/10/18
3	2017/07/16	2017/07/15
4	2017/11/05	2017/11/07
5	2017/12/07	2017/12/07
6	2018/02/09	2018/02/10
7	2018/02/25	2018/02/25
8	2018/03/13	2018/03/12
9	2018/10/23	2018/10/23
10	2019/01/11	2019/01/11
11	2019/04/17	2019/04/16

In Equation (1), $a_{i,j}$ and $b_{i,j}$ are the fitted regression coefficients, NDWI^{Fine}_{i,j,t} and NDWI^{Coarse} are the normalized difference water index (NDWI) [45] of fine and coarse resolution images at time t and pixel location (x, y), respectively. NDWI was calculated as the normalized difference of GREEN and near-infrared (NIR) bands (Equation (2)).

$$NDWI = (GREEN - NIR) / (GREEN + NIR),$$
(2)

We first resampled the coarse resolution NDWI image to the same resolution as the fine resolution NDWI imagery using the NEAREST interpolation method, i.e., resampled the 30 m Landsat NDWI to 10 m resolution, and then established the regression model based on the resampled Landsat NDWI and Sentinel-2 NDWI on a pixel-by-pixel basis. Using this model, higher resolution (10 m) NDWI images can be generated from any input of Landsat NDWI image. OTSU thresholding [46] was then applied to the resultant NDWI images to extract the surface water extent.

3.2. Water Volume Estimation

To calculate the relative water volume variation, the lake was assumed to be circular with a regular shape. In this study, we adopted the method used in [47] to estimate the lake volume change (ΔV), as shown in Equation (3).

$$\Delta V = \frac{1}{3} (H_1 - H_2) \cdot (A_1 + A_2 + \sqrt{A_1 \cdot A_2}), \tag{3}$$

where H_1 and A_1 represent the corresponding lake water level and area at time 1, and H_2 and A_2 are the water level and area at time 2, respectively.

3.3. Driving Factor Analysis

As the human activities had limited impacts on the water volume variation of Qinghai Lake [48], we assume there is no impact caused by anthropogenic factors and only analyze the climatic driving factors for lake water dynamics. Due to the complexity of climatic change and the diversity of influencing factors of lakes, nonlinear constraints and uncertainties are involved in the consideration of the impact of climate elements on the lake dynamics, which causes extensive greyness [49]. Therefore, the Grey Relation Analysis (GRA) [50] was applied to analyze the response of the water volume to climate factors.

The GRA uses the correlation of two sequences to characterize the degree of association between them, called the relational grade, which is calculated as:

$$R_{ij} = \frac{1}{N} \sum_{t=1}^{N} R_{ij}(t),$$
(4)

where R_{ij} represents the relational grade between the sequences of i and j, N is the length of the sequence, and $R_{ij}(t)$ is the correlation coefficient between the sequences of i and j at time t, calculated as Equation (5):

$$R_{ij}(t) = \frac{\Delta_{\min} + \rho \Delta_{\max}}{\Delta_{ij}(t) + \rho \Delta_{\max}},$$
(5)

where Δ_{min} and Δ_{max} denote the minimum and maximum of the absolute difference of two sequences at each time, respectively, $\Delta_{ij}(t)$ represents the absolute error between sequences at time t, and ρ is the resolution coefficient ($\rho \in (0, 1)$), usually set to 0.5 [49].

In addition, we adopted three different methods to calculate the correlation coefficient, namely Pearson [51], Spearman [51], and Kendall [51], to compare with the GRA analysis results. The Pearson correlation coefficient was also used to investigate the climate influence on water volume, which was calculated as Equation (6):

$$r = \frac{n \sum_{x_i y_i} - \sum_{x_i} \sum_{y_i}}{\sqrt{n \sum_{x^2} - (\sum_{x_i})^2} \sqrt{n \sum_{y^2} - (\sum_{y_i})^2}},$$
(6)

where *r* is the correlation coefficient ranging from -1 to 1, x and y are the values of the two variables, and n is the number of samples. While the absolution value of *r* is closer to 1, the correlation between variables is stronger.

4. Results

4.1. Validation of Downscaled Water Maps

We utilized a pair of Landsat 8 and Sentinel-2 images on 23 October 2018, which were not employed for establishing the downscaling model but to validate the downscaling method. A 10 m resolution water map was generated from a downscaled NDWI image derived from the Landsat 8 image using OTSU thresholding. Another 10 m resolution water map derived directly from the Sentinel-2 image was employed as the reference to validate the downscaled result. Two maps were generated by overlaying the water map derived from the original Landsat image and the downscaled result with the Sentinel-2 derived referencing water map, respectively (Figure 3). From these maps, it is obvious that the Landsat 8 image can accurately extract the major water body of Qinghai Lake, either with or without the downscaling process. The extraction differences are mainly distributed along the boundary, especially in Haixi Island, the estuaries of the Buha River and Shaliu River, the sandy area of Shadao Lake, and Haiyan Bay. Compared with the referencing Sentinel-2 water map, the water map derived from the original Landsat 8 image has many misclassified pixels, shown as red color for omission errors and green color for commission errors. The water map derived from downscaled Landsat 8 data showed some improvement, with more detailed features and small water bodies successfully being extracted, for example in the sandy area.



Figure 3. Comparison between Sentinel-2 and Landsat 8 water maps, (**a**) original Landsat 8 image, and (**b**) downscaled Landsat 8 image. Grey color (S2_land-L8_land) stands for pixels that were identified

as Land on Sentinel-2 image and Land on original/downscaled Landsat 8 image. Red color (S2_warer-L8_land) stands for pixels that were identified as Water on Sentinel-2 image and Land on original/downscaled Landsat 8 image (omission error). Green color (S2_land-L8_water) stands for pixels that were identified as Land on Sentinel-2 image and Water on original/downscaled Landsat 8 image (commission error). Blue color (S2_water-L8_water) stands for pixels that were identified as Water on Sentinel-2 image and Water on original/downscaled Landsat 8 image.

Based on these overlaying results (Figure 3), we calculated a confusion matrix by counting the number of four types of overlay map pixels. In this process, as both the reference and verification object are raster data, we took all the pixels as the samples to construct the confusion matrix, based on which accuracy indicators including commission error, omission error, overall accuracy, and Kappa coefficient were calculated (Table 3). It was found that the overall accuracy was clearly improved from 88.35% to 92.10%, and the commission error decreased by 2.46% and omission error by 1.94%. The Kappa coefficient was increased from 0.77 to 0.84. These accuracy indices suggest that the lake water was mapped more accurately by the downscaling method.

Table 3. The accuracy of water maps derived from the original Landsat 8 image and downscaled Landsat 8 image.

Accuracy Indicators	Landsat 8 Image	Downscaled Landsat 8 Image
commission error (%)	6.18	3.72
omission error (%)	5.47	3.53
overall accuracy (%)	88.35	92.10
Kappa coefficient	0.77	0.84

4.2. Lake Area and Shoreline Dynamics

We applied the downscaling model to generate 10 m resolution water maps from selected Landsat images for Qinghai Lake from 1991 to 2020. The lake water area exhibits a two-phase changing pattern as shown in Figure 4a. Taking 2004 as a turning point, the water area showed an overall downward trend at the first stage, dropping from 4316.20 km² in 1991 to 4199.23 km² in 2004. Since 2004, the water area of Qinghai Lake has been increasing gradually, reaching 4494.99 km² in 2020, with an annual growth rate of 18.49 km²/a.



Figure 4. (a) Annual water area of Qinghai Lake; (b) annual lake area derived from the Landsat image before and after downscaling, in comparison with that extracted from Hydroweb dataset (available for 1995–2017).

We compared the lake area derived from Landsat before and after downscaling with that extracted from the Hydroweb dataset (Figure 4b). Hydroweb only provides area estimation of Qinghai Lake from 1995 to 2017 through a combination of multiple satellite data such as Landsat and CBERS-2 [35]. The annual area was taken from the average value from May to November. It is shown in Figure 4b that the annual lake water areas are consistent among the three data sources. The Hydroweb area is overall slightly higher than the area derived from Landsat images, which may be accounted for by the area integrated by different remote sensing satellites. It is also observed that through the downscaling process, the Qinghai Lake area extracted by the Landsat images is closer to the observations of Hydroweb.

We took 1991, 2004, and 2020 to elaborate the spatial dynamics of Qinghai Lake shoreline (Figure 5). It can be seen clearly that the shoreline at the west, east, and north banks shrank in 2004 in comparison with 1991, particularly in the east bank. In 2004, Shadao Lake was separated from the main body of Qinghai Lake due to water receding. Compared with 2004, the water extent of Qinghai Lake in 2020 was much larger. The Shadao Lake and Haiyan Bay on the east was integrated with the main body of Qinghai Lake. The Tiebuka Bay, Buha River, and Haixi Island also expended significantly, but the Gahai Lake has not changed significantly. In addition, the shoreline on the south bank also had an apparent expansion from 2004 to 2020.



(b)

Figure 5. Shoreline change of Qinghai Lake for (a) 1991–2004, and (b) 2004–2020.

4.3. Lake Water Volume Variation

We extracted the annual average water level of Qinghai Lake from the Hydroweb dataset by taking the average water level from May to November each year. Due to the data availability, we only have the water level record from 1995–2020. The water level dropped from 3194.22 m in 1995 to 3193.62 m in 2004 with an average descending speed of 0.05 m/a, and then raised to 3197.20 m in 2020, with an average rate of 0.22 m/a. A significant correlation between the area and water level of Qinghai Lake was identified $(R^2 = 0.976, RMSE = 11.67, Figure 6a)$. Based on the regression model of water level and area, we estimated the water level of Qinghai Lake from 1991 to 1994 (red dots in Figure 6b) and made a full time series of the water level for 1991–2020 (Figure 6b). Similar to the

area variation, the water level variation of Qinghai Lake also exhibits a first-decline-thenincrease pattern. We fit a linear regression for the water level of 1991–2004 and 2004–2020, respectively, and found that both periods have significant linear trends, with R² both greater than 0.8.



Figure 6. (a) The area-level correlation; (b) The water level of the Qinghai Lake in 1991–2020.

Taking the water volume of 1991 as the baseline, the water volume dynamics in the past 30 years were calculated from water area and water level using Equation (3). As shown in Figure 7, it is clear that the water volume also shows a first-decline-then-increase pattern. We also fit a linear regression for the water volume variation in 1991–2004 and 2004–2020, respectively. It was found that both regression models have a high R^2 , suggesting significant linear trends. From these models, it is obvious that the water volume decreased from 1991 to 2004, with a fitted rate near to 0.38 km³/a, while it increased from 2004 to 2020, with a fitted rate of 0.89 km³/a.



Figure 7. 30-year water volume dynamics of Qinghai Lake based on water volume of 1991.

4.4. Driving Factors of Qinghai Lake Water Variation

In this paper, we calculated the annual accumulated temperature by selecting the daily temperature greater than 10 °C, which is proven to be increasingly important for assessing the impact of climate change [52].We adopted the Mann–Kendall (M–K) [53] trend analysis to identify the tipping point and trend of accumulated temperature, precipitation, and

evaporation from 1991 to 2017 in Qinghai Lake Basin (Figure 8). The M–K method is a nonparametric analysis method that has been extensively used for time-series hydrological analysis [54]. The results show that the annual accumulated temperature, precipitation, and evaporation in the Qinghai Lake Basin was overall increasing gradually. The tipping points of accumulated temperature and precipitation are 2005 and 2003, respectively, which is close to the turning point of the lake water volume. The average accumulated temperature in 1991–2005 is 1374.47 °C, which jumps to 1520.15 °C in 2005–2017. The average precipitation changes from 285.31 mm in 1991–2003 to 336.67 mm in 2003–2017. However, the change point of evaporation occurs in 1995. The average evaporation of 1991–1995 and 1995–2017 are 1669.86 mm and 1736.36 mm, respectively.



Figure 8. The change point and trend of accumulated temperature, precipitation, and evaporation from 1991 to 2017 in Qinghai Lake Basin.

We employed the GRA to investigate how the climatic elements have affected the relative water volume of Qinghai Lake in the past 30 years. The relational grade (Table 4) between the annual accumulated temperature, precipitation, and evaporation, and the water volume of Qinghai Lake was obtained through Equations (4) and (5). In addition, three different correlation analysis methods (i.e., Pearson, Kendall, and Spearman) were adopted for cross comparison.

	Accumulated Temperature	Precipitation	Evaporation
Pearson	0.25	0.46 *	-0.26
Kendall	0.12	0.28	-0.14
Spearman	0.14	0.40 *	-0.23
Relational grade	0.56	0.95	0.51

Table 4. The correlation of annual mean values of accumulated temperature, precipitation, and evaporation with the annual water volume.

Note: * *p* < 0.05.

According to the results of three different correlation analyses, the correlation of precipitation is the highest no matter which method is applied. The correlation between water volume and accumulated temperature is relatively low, while that with evaporation is negative. The relational grade of GRA also suggests that precipitation has the greatest impact on the water volume, with a relational grade of 0.95. The accumulated temperature has a value of 0.56, and evaporation exerts the weakest effect on water volume dynamics, with a relational grade of 0.51.

To further explore the relationship between climate factors and Qinghai Lake water volume, we performed the Pearson analysis in 1991–2004 and 2004–2017 separately (Table 5). During the period of 1991–2004, it seems that the accumulated temperature is the major factor affecting the decline of Qinghai Lake water volume. For the period of 2004–2017, the increase of water volume seems to be mainly positively affected by the precipitation, with the correlation coefficient close to 0.6 and p < 0.05.

Table 5. Pearson's r between climate factors and water volume for period 1991–2004 and 2004–2017.

Period	Accumulated Temperature	Precipitation	Evaporation
1991-2004	-0.70 **	0.12	-0.24
2004-2017	0.36	0.60 *	-0.32

Note: * *p* < 0.05; ** *p* < 0.01.

5. Discussion

As the largest inland saline lake on the plateau in China, Qinghai Lake not only regulates the local climate through the "lake effect", but also directly affects the wetlands and sandy land around the lake. This study made full use of the continuity of the mediumto high-resolution Landsat imagery and combined them with higher-resolution Sentinel-2 imagery for more accurate and long-term monitoring of Qinghai Lake water area dynamics. Meanwhile, the water level data acquired by satellite altimetry were employed to transform the Landsat-based water area dynamics to water volume dynamics. The results show that the water area, water level, and water volume of Qinghai Lake from 1991 to 2020 all exhibit a first-decline-then-increase pattern. The turning point occurred in 2004, when the water level and area reached the minimum. Since then, Qinghai Lake has entered into a period of stable expansion. Overall, our findings were found to be consistent with previous studies [23,24,48,55,56]. However, compared with the annual average water level obtained from gauge stations of Qinghai Lake by Li et al. [42], the water level of the Hydroweb dataset is relatively higher. Due to the lack of lake bathymetry dataset, the water volume estimated in this study only represents the water volume change relative to 1991, instead of the real water volume change. Moreover, different altimetry data have different uncertainties due to their different data quality. In the future, we will consider combining the lake bathymetry and fusing different altimetry satellite data to deepen the research on water level and water volume.

Existing studies have proven that local climate change in the Qinghai Lake Basin in recent years leads to gradual increases in temperature and precipitation and decreases in evapotranspiration [48,57]. Zhang et al. [37] found that increased net precipitation contributes the majority of the water supply (74%) for the lake volume increase, followed by glacier mass loss (13%) and ground ice melt due to permafrost degradation (12%) on

the Tibetan Plateau from 2003–2009. Song et al. [58] also pointed out that the meltwater from mountainous glaciers and snow cover have become important water sources for Qinghai Lake, supported by the work of Zhang et al. [33]. Considering the increasing contribution of glaciers and precipitation to the water balance, it is anticipated that the water volume of the plateau inland lakes will continue to increase in the next few decades. We also found that the increasing precipitation had a major contribution to the increase of Qinghai Lake's water volume, indicating possible continuous water increasing in the near future [59]. Continuous rising of water level and expansion of water area may breed a better ecological environment and richer biodiversity, which would be beneficial for local ecological protection and desertification prevention [48].

6. Conclusions

We integrated Landsat and Sentinel-2 remote sensing imagery to construct a long-term 10 m resolution lake water area variation series, which was further associated with the Hydroweb water level dataset to estimate the water volume change. Through this process, we were able to provide the highest resolution long-term Qinghai Lake water monitoring results to date. The driving factors of lake water variation were further analyzed through the grey theory. Based on the results, we draw the following conclusions.

(1) The spatial downscaling method that was incorporated with the Sentinel-2 and Landsat imagery can effectively take advantage of Landsat's long time series and Sentinel-2's high spatial resolution and thus achieve long-term and high-resolution lake monitoring. The resultant water extent was proven to have an improved overall accuracy of 92.10% and Kappa coefficient of 0.84.

(2) The area, water level, and water volume of the Qinghai Lake exhibit the same first-decline-then-increase pattern, with 2004 as the turning point. The minimum lake area that occurred in 2004 is 4199.23 km², and the maximum is 4494.99 km² in 2020. The water level dropped from 3194.22 m in 1995 to 3193.62 m in 2004 with an average descending speed of 0.05 m/a, and then raised to 3197.20 m in 2020, with an average rate of 0.22 m/a. The water volume decreased between 1991 and 2004, with a fitted rate of 0.34 km³/a, while it increased between 2004 and 2020, with a fitted rate of 0.89 km³/a.

(3) The results of the GRA and three correlation analyses all indicate that precipitation has the greatest impact on the water volume variation of Qinghai Lake, followed by accumulated temperature and evaporation. From 1991–2004, the Pearson correlation analysis indicates that accumulated temperature is the primary factor affecting the decline of Qinghai Lake water volume, while the increase of water volume from 2004–2017 seems to be mainly positively affected by precipitation.

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