Spatiotemporal Variation and Influencing Factors of Water-Carbon Variables in the Qinghai Lake Basin over the Past 25 Years

Yan Pengxu, Zhang Lihua, Zeng Fanxing, Bai Xiaohui, Ye Yang, Cao Tiejie

2026-08-24

ChinaRxiv

Abstract

The Qinghai Lake Basin is a typical alpine mountainous endorheic river basin on the northeastern margin of the Qinghai-Tibet Plateau. Studying its water-carbon coupling mechanism is of great significance for revealing the patterns of carbon-water interactions in alpine ecosystems and supporting the coordinated management of water resources and carbon sinks. Based on multi-source remote sensing and meteorological data from 2000 to 2024, this study took net primary productivity (NPP), evapotranspiration (ET), and water use efficiency (WUE) as core variables, systematically analyzed their spatiotemporal variation characteristics, and integrated the dual machine learning methods of Random Forest and XGBoost to examine the driving mechanisms from both spatial and temporal dimensions. The results show that: (1) In terms of temporal variation, over the past 25 a, both NPP and ET in the basin exhibited significant upward trends, with growth rates of 2.511 g C·m-2·a-1 and 4.470 mm·a-1, respectively, while WUE showed a nonlinear pattern of first decreasing and then increasing, with 2017 as the turning point. (2) In terms of spatial distribution, NPP and WUE showed a pattern of "high in the southeast and low in the northwest," whereas ET exhibited a "high in the north and low in the south" distribution, indicating significant spatial heterogeneity. (3) At the spatial scale, elevation significantly controlled the spatial differentiation of NPP and WUE but had no significant effect on ET; vegetation type dominated the spatial differences in NPP and WUE, with marshes, cultivated vegetation, grasslands, and shrublands showing higher carbon sequestration capacity and water use efficiency; air temperature and leaf area index (LAI) had significant positive driving effects on NPP, precipitation and air temperature jointly regulated ET, and WUE was significantly negatively correlated with precipitation. (4) At the temporal scale, LAI was the core driver of NPP variation (RF feature importance: 0.467; XGBoost: 0.337), ET was jointly regulated by LAI and precipitation, and WUE was more sensitive to moisture conditions such as precipitation and water area, with substantially greater difficulty in model explanation than single water-carbon variables. The findings reveal the spatiotemporal-scale driving patterns of water-carbon coupling in alpine endorheic river basins and can provide a scientific basis for ecological protection and integrated management of water-carbon resources on the Qinghai-Tibet Plateau.

Full Text

Spatiotemporal Variation and Influencing Factors of Water-Carbon Variables in the Qinghai Lake Basin over the Past 25 Years

Yan Pengxu[1], Zhang Lihua[1,2], Zeng Fanxing[3], Bai Xiaohui[1], Ye Yang[1], Cao Tiejie[1]

(1. College of Geography and Environmental Science, Northwest Normal University, Lanzhou 730070, Gansu, China; 2. Key Laboratory of Resource Environment and Sustainable Development of Oasis, Gansu Province, Lanzhou 730070, Gansu, China; 3. Melbourne Institute of Technology, Fuzhou University, Fuzhou 350108, Fujian, China)

Abstract: The Qinghai Lake Basin is a typical alpine inland river basin on the northeastern margin of the Qinghai–Tibet Plateau. Studying its water–carbon coupling mechanism is of great significance for revealing the patterns of carbon–water interactions in alpine ecosystems and for supporting the coordinated management of water resources and carbon sinks. Based on multi-source remote-sensing and meteorological data from 2000 to 2024, and taking net primary productivity (NPP), evapotranspiration (ET), and water-use efficiency (WUE) as core variables, this study systematically analyzed their spatiotemporal variation characteristics and integrated random forest and XGBoost machine-learning methods to analyze driving mechanisms from both spatial and temporal dimensions. The results show that: (1) In terms of temporal variation, NPP and ET in the basin over the past 25 years both showed significant increasing trends, with growth rates of 2.511 g $C \cdot m^{-2} \cdot a^{-1}$ and 4.470 $mm \cdot a^{-1}$, respectively; WUE exhibited nonlinear change, decreasing first and then increasing, with 2017 as the turning point. (2) In terms of spatial distribution, NPP and WUE showed a pattern of "high in the southeast and low in the northwest," whereas ET showed a distribution of "high in the north and low in the south," with significant spatial heterogeneity. (3) At the spatial scale, elevation significantly controlled the spatial differentiation of NPP and WUE but had no significant effect on ET; vegetation type dominated the spatial differences of NPP and WUE, with wetlands, cultivated vegetation, grasslands, and shrubs having higher carbon sequestration capacity and water-use efficiency; air temperature and leaf area index (LAI) significantly and positively drove NPP, precipitation and air temperature jointly regulated ET, and WUE was significantly negatively correlated with precipitation. (4) At the temporal scale, LAI was the core driving factor of NPP variation (RF feature importance 0.467, XGBoost 0.337), ET was jointly regulated by LAI and precipitation, and WUE was more sensitive to water conditions such as precipitation and water-body area; the explanatory difficulty of the models was significantly higher than that for a single water–carbon variable. The study results reveal the spatiotemporal-scale driving patterns of water–carbon coupling in alpine inland river basins and can provide scientific evidence for ecological protection and integrated management of water and carbon resources on the Qinghai–Tibet Plateau.

Keywords: Qinghai Lake Basin; water–carbon coupling; net primary productivity; evapotranspiration; water-use efficiency

Article number: 1000-6060(2026)08-1572-15(1572~1586)

Terrestrial ecosystem carbon cycling and water cycling have strong coupling relationships[1]. The water–carbon cycle is the core of terrestrial material and energy cycling, and revealing its coupling mechanism is the basis for realizing integrated management of water and carbon resources. At the basin scale, water-carbon coupling is mainly manifested in the consumption of soil water by vegetation carbon sequestration processes and in the regulation of runoff generation, the scouring and transport of surface organic matter by precipitation and runoff processes, etc.[2]; this process is directly related to water resources and ecosystem service functions[3]. Water-carbon variables are core flux indicators of the water-carbon cycle and their coupling relationship, and studying water-carbon variables means examining the changing patterns of the water-carbon cycle and their interactions. Therefore, analyzing the variation characteristics and influencing factors of basin-scale water-carbon variables is of great significance for the development of climatology, hydrology and water resources, the ecological environment, and other fields.

At present, water-cycle research mostly focuses on the interactions among climate, vegetation, human activities, and the water cycle, as well as the responses of climate and land-use change factors and evapotranspiration (ET)[4-6]; carbon-cycle research mainly analyzes the spatiotemporal variation of net primary productivity (NPP) in basins and estimates carbon-sink fluxes[7-8]; water-carbon coupling research mainly analyzes the spatiotemporal variation of water-use efficiency (WUE), with the help of vegetation and meteorological factors to explore its driving factors[9-10]. However, in research on the influencing factors of water-carbon variables, most studies focus only on a single water-carbon variable and concentrate on temporal-scale factors such as air temperature, precipitation, wind speed, solar radiation, and leaf area index (LAI)[11-14]; studies on the influence of spatial-scale factors such as elevation and vegetation type are not abundant. It is worth noting that surface water is not only an important component of water resources and plays a key role in water-supply regulation and ecological balance; water-body area, as an important feedback form, is also an important indicator characterizing the health of lake-basin ecosystems[15-17] and plays an important driving role in basin water-carbon coupling regulation, yet this point is often overlooked in existing studies. In addition, at the methodological level,

Received: 2025-10-29; **Revised:** 2025-11-24
Funding: Supported by the National Natural Science Foundation of China (41761043, 41201196); Gansu Provincial Science and Technology Plan Project (20YF3FA042)
Author biography: Yan Pengxu (2004-), male, undergraduate student, mainly engaged in physical geography research. E-mail: ypengxuy@163.com
Corresponding author: Zhang Lihua (1980-), female, PhD, associate professor, mainly engaged in research on ecological responses under climate change. E-mail: zhanglihualz@126.com

Existing studies have often used traditional methods such as principal component analysis and grey relational analysis. However, these methods are constrained by linear assumptions and their unsupervised nature, making it difficult to directly quantify the marginal contribution of each factor to key hydrocarbon variables. In comparison, random forest (RF) and XGBoost can output ecologically interpretable rankings of variable importance through decision-tree regression analysis of variable contributions, thereby effectively identifying dominant factors and key thresholds[^18].

The Qinghai Lake Basin is located in the northeastern Qinghai-Tibet Plateau. It is a typical alpine inland river basin with a fragile ecosystem and belongs to a globally climate-change-sensitive region[^19-^21]. In recent decades, against the background of regional warming-wetting and lake expansion, vegetation in the basin has gradually improved, hydrological processes have been markedly adjusted, and the coupled evolution characteristics of water and carbon elements have become prominent. At present, independent studies of the water cycle and carbon cycle in the basin are relatively abundant, but studies on hydrocarbon coupling—especially long-term analyses of hydrocarbon coupling relationships and driving mechanisms in alpine inland river basins—remain relatively scarce. Therefore, carrying out research on the hydrocarbon coupling mechanism in the Qinghai Lake Basin is of great significance for revealing the response patterns of regional ecosystems to climate change and supporting ecological protection and water-resources management; it can also provide a scientific reference for hydrocarbon coupling studies in similar basins on the Qinghai-Tibet Plateau.

Based on the above, this paper takes the Qinghai Lake Basin as the study area; selects NPP as the carbon variable, ET as the water variable, and WUE as the hydrocarbon-coupling variable; and analyzes the spatiotemporal variation characteristics of these hydrocarbon variables over the past 25 years (2000-2024). On this basis, the effects of altitude, vegetation type, meteorological factors (air temperature, precipitation, wind speed, and solar radiation), and LAI are explored at the spatial scale, and the driving mechanisms of meteorological factors, LAI, and water-body area are analyzed at the temporal scale. The aim is to reveal the intrinsic laws of hydrocarbon coupling in the Qinghai Lake Basin and the interaction mechanisms between the water cycle and carbon cycle, thereby providing theoretical support for ecological protection and water-resources management in the Qinghai Lake Basin and even on the Qinghai-Tibet Plateau.

1 Data and Methods

1.1 Overview of the Study Area

Qinghai Lake is the largest saline lake and inland lake in China. It is located in the northeastern Qinghai-Tibet Plateau, spanning Haiyan, Gangcha, Gonghe, and three other counties in Haibei and Hainan Tibetan Autonomous Prefectures, and was formed in the tectonic fault depression on the northeastern margin of the Qinghai-Tibet Plateau[^22]. The Qinghai Lake Basin (97°50′-101°20′ E, 36°15′-38°20′ N) has a total area of approximately 29,661 km^2 and an elevation of 3,109-5,290 m (Fig. 1a). Because of its high elevation and strong solar radi-

Fig. 1 Schematic diagram of the study area

Figure 1: Fig. 1 Schematic diagram of the study area

ation, it has a typical plateau continental climate, with simultaneous rainy and hot seasons and distinct dry and wet seasons. The water system of the Qinghai Lake Basin is composed mainly of Qinghai Lake and its principal inflowing rivers, including the Buha River, Shaliu River, Haergai River, and Quanji River (Fig. 1a). The main vegetation types in the basin include coniferous forest, shrubland, grassland, meadow, alpine vegetation, and cultivated vegetation (Fig. 1b). Among them, meadow occupies the largest area, accounting for 66.13%; grassland accounts for 18.4%; and coniferous forest has the smallest area, accounting for only 0.11% (Table 1). In addition, the basin is an important permafrost distribution area: the northwestern part is a multi-year permafrost zone, while the central part and the areas around the lake are seasonal permafrost zones[^22].

Fig. 1 Schematic diagram of the study area

Table 1 Area and proportion of different vegetation types in the Qinghai Lake Basin

Indicator	Coniferous forest	Shrubland	Desert	Grassland	Meadow	Marsh	Alpine vegetation	Cultivated vegetation	Other
Area/km^2	28.00	1707.00	883.00	4623.00	16612.00	51.00	914.00	239.00	63.00
Proportion/%	0.11	6.80	3.52	18.40	66.13	0.20	3.64	0.95	0.25

1.2 Data Sources and Processing

The NPP, ET, and LAI data were obtained from MODIS products (MOD17A3, MOD16A3, and MOD15A2) of the U.S. Earth Observing System. Air temperature, precipitation, and solar radiation data were based on the ERA5-Land reanalysis dataset on the GEE platform. Elevation data were obtained from the ASTER GDEM V3 global digital elevation model dataset in the Geospatial Data Cloud (https://www.gscloud.cn/). Wind speed and vegetation-type data were obtained, respectively, from the China 0.01° resolution annual wind-speed raster data and the "China 1:1,000,000 Vegetation Dataset" of the National Cryosphere Desert Data Center (https://www.ncdc.ac.cn/). This dataset classifies China' s vegetation into 11 vegetation-type groups, 54 vegetation types, and 796 formations and subformations. As a current vegetation map, it can reflect the recent quality status of vegetation in China. In this study, the above data were uniformly summarized as annual mean data in ArcGIS 10.8.1, projected (WGS 1984), and resampled to a unified resolution (500 m). Finally, vector clipping tools were used to obtain data for nearly 25 years in the Qinghai Lake Basin (Table 2).

Table 2 Data information and sources

Tab. 2 Data information and sources

Data	Unit	Spatial resolution	Data source	Years
Net primary productivity (NPP)	$g\ C \cdot m^{-2}$	500 m	MOD17A3	2000—2024
Evapotranspiration (ET)	mm	500 m	MOD16A3	2000—2024
Elevation	m	30 m	ASTER GDEM V3	-
Vegetation type	-	1 km	China 1:1,000,000 Vegetation Dataset	2023
Air temperature	℃	1 km	ERA5-Land reanalysis dataset	2000—2024
Precipitation	mm	1 km	ERA5-Land reanalysis dataset	2000—2024
Solar radiation	$MJ \cdot m^{-2}$	1 km	ERA5-Land reanalysis dataset	2000—2024
Wind speed	$m \cdot s^{-1}$	0.01°	China 0.01° resolution annual wind-speed raster data	2000—2024
Leaf area index (LAI)	-	500 m	MOD15A2	2000—2024

WUE was calculated using the ratio of NPP to ET. It represents the water consumed by plants per unit of fixed carbon and is an important indicator characterizing the degree of carbon-water coupling in ecosystems[1], with units of $g\ C \cdot m^{-2} \cdot mm^{-1}$. Water-body area was extracted year by year in ENVI 5.6 based on the reflectance of the green and near-infrared bands in the Qinghai

[1] 22

Lake Basin. The normalized difference water index (NDWI) was obtained using band calculations, and preliminary extraction was performed with a fixed threshold of 0.2. This was supplemented by visual interpretation of random validation points and confusion-matrix accuracy assessment, thereby obtaining annual water-body area[2], with a spatial resolution of 500 m and units of km^2.

1.3 Research Methods

1.3.1 Trend Analysis

This study conducted time-series change analysis of the water–carbon variables (NPP, ET, and WUE) and their influencing factors at the temporal scale (air temperature, precipitation, water-body area, and LAI). Based on the attributes of raster data layers, annual mean values of each indicator were obtained; inter-annual change statistics were performed using OriginPro 2024; and the Theil-Sen Median slope estimator and Mann-Kendall trend method were used to analyze trends in the time series. This method can improve computational efficiency and effectively handle outliers[3]. Trend significance was tested using the t test, and trend significance was determined at the 95% confidence level.

At the spatial scale, based on annual mean raster maps, pixel-by-pixel trend analysis was performed using Sen' s slope and the Mann-Kendall test. Each pixel was then divided into five categories according to the following criteria: significant increase (slope > 0, $P < 0.01$), non-significant increase (slope > 0, $P \geq 0.01$), significant decrease (slope < 0, $P < 0.01$), non-significant decrease (slope < 0, $P \geq 0.01$), and stable/unchanged ($|\text{slope}| \leq \epsilon$, where ϵ is the 10th percentile of the absolute values of the slopes of all valid pixels in the basin). From this, the spatial distribution of multi-year change trends and the spatial pattern of multi-year mean values for each variable were obtained. In the spatial analysis, the significance level was set to $\alpha = 0.01$ to control the false-positive errors caused by multiple comparisons; the threshold for stability/unchanged was determined using the variable-adaptive quantile method to avoid the influence of quantitative-scale differences[4].

1.3.2 Analysis of Major Influencing Factors at the Spatial Scale

In this study, zonal statistics were performed on the multi-year mean raster maps of NPP, ET, and WUE together with elevation maps and vegetation-type maps, obtaining the characteristics of the water–carbon variables under different elevations and vegetation types. Meanwhile, Matlab was used to conduct partial-correlation analysis between the spatial distributions of multi-year meteorological factors and each water–carbon variable in the Qinghai Lake Basin, and to calculate higher-order partial-correlation coefficients. Partial-correlation analysis can analyze the independent correlation between two variables while

[2] 23
[3] 24
[4] 25-26

controlling for the influence of other variables, thereby eliminating inter-factor interference and more accurately identifying the true influence of a single meteorological element on water-carbon variables[5]. Suppose there are k $(k > 2)$ variables. Under the condition of controlling the influence of g $(g \leq k-2)$ variables, the g-order partial-correlation coefficient between variables x_i and x_j is:

$$r_{ij\cdot l_1 l_2 \cdots l_g} = \frac{r_{ij\cdot l_1 l_2 \cdots l_{g-1}} - r_{il_g\cdot l_1 l_2 \cdots l_{g-1}} r_{jl_g\cdot l_1 l_2 \cdots l_{g-1}}}{\sqrt{\left(1 - r^2_{il_g\cdot l_1 l_2 \cdots l_{g-1}}\right)\left(1 - r^2_{jl_g\cdot l_1 l_2 \cdots l_{g-1}}\right)}} \tag{1}$$

In the formula, $r_{ij\cdot l_1 l_2 \cdots l_g}$ is the partial-correlation coefficient between variable i and variable j after controlling for variables $l_1, l_2, \cdots, l_g$; the rest can be inferred analogously. Finally, the t test was used for significance testing ($\alpha = 0.05$), and the results were divided into five correlation types: significant positive correlation, non-significant positive correlation, non-significant negative correlation, significant negative correlation, and no data.

1.3.3 Analysis of Major Influencing Factors at the Temporal Scale

RF originates from classification and regression trees (CART) and is an ensemble-learning method using multiple decision trees. RF generates multiple training datasets through Bootstrap resampling,

in each subset, and the optimal variable is selected from the randomly sampled feature subset for node splitting[^28]. In the study, repeated training was conducted by setting the number of decision trees, `ntree`, to find the optimal parameter, `mtry`. XGBoost is a machine-learning method based on Boosting ensemble learning. This algorithm uses CART as its base classifier, progressively adding new trees to fit the residuals from the previous round of prediction, and finally accumulates the predictions of all trees to generate the final predicted value. In addition to RF and XGBoost, this study also conducted parallel analyses using support vector regression (SVR), traditional gradient boosting decision trees (GBDT), LightGBM, CatBoost, and a deep neural network (MLP). This strategy can not only avoid bias from selecting a single model, but also provide a basis for subsequent model fusion and engineering deployment. SVR is sensitive to kernel functions and hyperparameters, is prone to overfitting with small samples, and has high computational complexity[^29]; GBDT has strong fitting ability, but is sensitive to high-dimensional features and noise, lacks regularization, is prone to overfitting, and requires manual handling of missing values[^30]; LightGBM and CatBoost are efficient in big-data scenarios, but are susceptible to noise interference and depend on sufficient category samples when the sample size is insufficient[^31-32]; MLP requires normalization and complex tuning, and its training time is far longer than that of tree models[^32]. By comparison, RF naturally suppresses overfitting through the dual randomness of Bootstrap

[5] 27

and random feature subsets, is highly robust to missing values and outliers, and can provide stable baselines and interpretable variable importance under small-sample conditions[^29]; XGBoost, supported by regularization (L1/L2), second-order Taylor expansion, and distributed parallel training, significantly improves prediction accuracy and efficiency in nonlinear scenarios, and can achieve both global and local interpretability through SHAP[^31]. Therefore, the complementary use of RF and XGBoost can effectively cover different data scales and interpretability requirements in analyzing the driving mechanisms of water-carbon variables in the Qinghai Lake Basin.

2 Results and Analysis

2.1 Temporal variation characteristics of water-carbon variables in the Qinghai Lake Basin

From 2000 to 2024, NPP and ET in the Qinghai Lake Basin both showed significant increasing trends (Fig. 2), with growth rates of 2.511 g $C \cdot m^{-2} \cdot a^{-1}$ and 4.470 $mm \cdot a^{-1}$, respectively. WUE, taking 2017 as the breakpoint, showed a nonlinear trend of first decreasing and then increasing, with rates of decrease and increase of 0.007 g $C \cdot m^{-2} \cdot mm^{-1} \cdot a^{-1}$ and 0.013 g $C \cdot m^{-2} \cdot mm^{-1} \cdot a^{-1}$, respectively. In addition, the minimum and maximum values of NPP were 186.556 g $C \cdot m^{-2}$ and 279.483 g $C \cdot m^{-2}$, occurring in 2001 and 2024, respectively; the minimum and maximum values of ET occurred in 2000 and 2017, respectively, at 334.74 mm and 522.72 mm; the minimum WUE was 0.448 g $C \cdot m^{-2} \cdot mm^{-1}$ in 2017, while higher values occurred in 2000 and 2024, at 0.593 g $C \cdot m^{-2} \cdot mm^{-1}$ and 0.583 g $C \cdot m^{-2} \cdot mm^{-1}$, respectively. The fluctuations in WUE mainly arose from the relative changes in the growth rates of NPP and ET: in 2000 and 2024, NPP increased faster than ET and WUE rose; in the intervening years, the growth rate of NPP slowed or declined, while ET increased faster or decreased only slightly, and WUE correspondingly declined.

Note: ρ^2 is the Spearman effect size reflecting the monotonic trend of an indicator over time; * indicates that the Sen' s slope for each water-carbon factor passed the 0.05 significance-level test. The same below.

Fig. 2 Interannual variations in water and carbon variables in the Qinghai Lake Basin

2.2 Spatial distribution characteristics of ET, NPP, and WUE in the Qinghai Lake Basin

From 2000 to 2024, the distribution patterns and changing trends of NPP, ET, and WUE in the Qinghai Lake Basin all showed obvious spatial differentiation. In terms of the multi-year mean spatial distribution pattern (Fig. 3), the distributions of NPP and WUE were relatively…

(a) NPP

Legend

NPP/g C • m^{-2}

0–129
129–213
213–286
286–374
374–591
Qinghai Lake Basin boundary

0 60 km

(b) ET

Legend

ET/mm

347–439
439–482
482–525
525–567
567–807
Qinghai Lake Basin boundary

0 60 km

(c) WUE

Legend

WUE/g C • m^{-2} • mm^{-1}

0.02–0.27
0.27–0.45
0.45–0.61
0.61–0.79
0.79–1.24
Qinghai Lake Basin boundary

0 60 km

Fig. 3 Spatial distribution patterns of water and carbon variables in the Qinghai Lake Basin

Similarly, all show the characteristic of being high in the southeast and low in the northwest; ET decreases gradually from north to south. Among them, the high-value regions of NPP and WUE (>286 g C • m^{-2} and >0.61 g C • m^{-2} • mm^{-1}) are mainly distributed in the lakeshore areas of Qinghai Lake, accounting for 29% and 25% of the basin area excluding water bodies, respectively. The low-value regions (<213 g C • m^{-2} and <0.45 g C • m^{-2} • mm^{-1}) are mainly distributed in the northwestern region, accounting for 46% and 45%, respectively. The high-value region of ET (>525 mm) accounts for 15% of the basin area excluding water bodies, mainly distributed in the northern region, whereas the low-value region (<482 mm) accounts for 59%, mainly distributed in the western and southern regions.

In terms of change trends (Fig. 4), over the past 25 a, NPP, ET, and WUE have shown increasing trends in most areas of the basin, with more than 70% of the regions for NPP and ET showing significant increases. In addition, about 10% of the areas in the northwestern and southeastern parts of the basin show decreasing or stable trends for NPP; more than 10% of the areas in the northern part of the basin show stable trends for ET. Compared with NPP and ET, WUE has a larger spatial variation amplitude, with nearly 30% of the areas around the lake showing significant decreases, nonsignificant decreases, or stable trends.

2.3 Analysis of spatial influencing factors of water and carbon variables in the Qinghai Lake Basin

Considering elevation, NPP and WUE show a consistent

(a) NPP

0 60 km

(b) ET

0 60 km

(c) WUE

Legend

Qinghai Lake Basin boundary

0 60 km

Change trend

Significant decrease Nonsignificant decrease Stable/no change Nonsignificant increase Significant increase

Fig. 4 Spatial change trends of water and carbon variables in the Qinghai Lake Basin

a certain negative correlation: in places with lower elevation, NPP and WUE are higher, whereas in places with higher elevation, NPP and WUE are lower; ET shows no obvious association with elevation (Fig. 5). Combined with vegetation types, the NPP and WUE of grassland, shrubland, and cultivated vegetation are relatively high, while ET differs little among different vegetation types (Fig. 6). Thus, this paper further verifies the relationships between water–carbon variables and elevation and vegetation type.

As elevation increases, both NPP and WUE show a gradually decreasing trend, and the rate of decrease increases markedly in the 3600–3900 m interval, continuing until 4500 m before gradually leveling off. ET shows a certain increasing trend with increasing elevation, but overall it is not significant (Fig. 5). The multi-year mean NPP and WUE of different vegetation types differ, but their order of magnitude is basically consistent (Fig. 6). The ranking of NPP among different vegetation types is marsh

Fig. 5 Effect of elevation on water and carbon variables in the Qinghai Lake Basin

Panels: (a) NPP; (b) ET; (c) WUE.
Horizontal axis: elevation/m.
Legends: NPP, ET, WUE; variation trend curve.
Vertical axes: NPP/g C · m^{-2}; ET/mm; WUE/g C · m^{-2} · mm^{-1}.

Fig. 6 Effect of vegetation types on water and carbon variables in the Qinghai Lake Basin

Panels: (a) NPP; (b) ET; (c) WUE.
Horizontal axis: vegetation type.
Vegetation types shown: coniferous forest, shrubland, desert, grassland, meadow, marsh, alpine vegetation, cultivated vegetation, other.
Vertical axes: NPP/g C · m^{-2}; ET/mm; WUE/g C · m^{-2} · mm^{-1}.

(376 g C · m^{-2}) > cultivated vegetation (337 g C · m^{-2}) > shrubland (289 g C · m^{-2}) > grassland (285 g C · m^{-2}) > coniferous forest (258 g C · m^{-2}) > meadow (217 g C · m^{-2}) > desert (96 g C · m^{-2}) > alpine vegetation (95 g C · m^{-2}) > other (65 g C · m^{-2}); whereas the WUE ranking was marsh (0.85 g C · m^{-2} · mm^{-1}) > cultivated vegetation (0.75 g C · m^{-2} · mm^{-1}) > grassland (0.64 g C · m^{-2} · mm^{-1}) > shrubland (0.62 g C · m^{-2} · mm^{-1}) > coniferous forest (0.61 g C · m^{-2} · mm^{-1}) > meadow (0.45 g C · m^{-2} · mm^{-1}) > desert (0.22 g C · m^{-2} · mm^{-1}) > alpine vegetation (0.19 g C · m^{-2} · mm^{-1}) > other (0.13 g C · m^{-2} · mm^{-1}); the differences in ET among different vegetation types were not significant. This further verifies the judgment made above in combination with Fig. 1.

By calculating the partial correlation coefficients between meteorological factors and LAI and each water-carbon variable in the Qinghai Lake Basin, the spatial response relationships of NPP, ET, and WUE at the climate and vegetation levels can be analyzed (Fig. 7). In terms of NPP–

(a) Partial correlation between NPP and air temperature

(b) Partial correlation between ET and air temperature

(c) Partial correlation between WUE and air temperature

(d) Partial correlation between NPP and precipitation

(e) Partial correlation between ET and precipitation

(f) Partial correlation between WUE and precipitation

(g) Partial correlation between NPP and wind speed

(h) Partial correlation between ET and wind speed

(i) Partial correlation between WUE and wind speed

(j) Partial correlation between NPP and LAI

(k) Partial correlation between ET and LAI

(l) Partial correlation between WUE and LAI

(m) Partial correlation between NPP and solar radiation

(n) Partial correlation between ET and solar radiation

(o) Partial correlation between WUE and solar radiation

Legend: Qinghai Lake Basin boundary

Partial-correlation significance: significant positive correlation; nonsignificant positive correlation; nonsignificant negative correlation; significant negative correlation; no data.

Fig. 7 Spatial influencing factors and partial correlation analysis of water and carbon variables in the Qinghai Lake Basin

In terms of NPP, temperature and LAI exerted significant positive driving effects on it. The areas with significant positive correlations for temperature were concentrated in the western, central, and southern parts of the basin, while those for LAI covered the entire basin; the proportions of areas with significant positive correlations for the two reached 53% and 76%, respectively. The effects of precipitation and wind speed on NPP were not significant overall, with only small local areas showing significant negative or positive correlations. The proportion of areas with significant negative correlation for solar radiation reached 22%. For ET, the areas with significant positive correlations for LAI and temperature accounted for 57% and 31%, respectively; precipitation in the central and northern parts of the basin was also significantly positively correlated with ET, accounting for 20%, making it an important factor regulating ET in this region. Wind speed was not significant overall for ET, and solar radiation showed only a slight negative effect; both contributed relatively little to the spatial differentiation of ET. For WUE, the independent driving effect of any single factor was not prominent; overall, the coupled influence of multiple factors was more evident. Among them, precipitation was significantly negatively correlated with WUE, with correlated areas accounting for 30%, and the effect was relatively pronounced in the western part of the basin, making it a comparatively prominent influencing factor. LAI was significantly positively correlated with WUE only in the periphery of the basin, with an area proportion of 21%. Although wind speed was positively correlated with WUE in most areas, the significant proportion was only 5%. The correlations between the remaining factors and WUE were relatively weak, and their spatial influence was not obvious.

2.4 Analysis of Temporal Influencing Factors of Water-Carbon Variables in the Qinghai Lake Basin

Among the interannual changes in the temporal influencing factors of water-carbon variables in the Qinghai Lake Basin, temperature, precipitation, wind speed, water body area, and LAI all showed significant upward trends, whereas solar radiation showed a nonsignificant downward trend (Figure 8). Temperature increased year by year at a rate of 0.035 ℃ · a^-1; the minimum value, −3.409 ℃, occurred in 2004, and the maximum value, −1.046 ℃, occurred in 2024. Precipitation increased at a rate of 3.595 mm · a^-1, with a fluctuation range of 553.550–763.223 mm; the extreme values occurred in 2013 and 2018, respectively, with a short time interval. Wind speed increased at a rate of 0.010 m · s$^{-1 \cdot a}$-1, reaching the minimum value of 1.993 m · s^-1 and the maximum value of 2.465 m · s^-1 in 2014 and 2023, respectively. The water body area increased by an annual average of 17.663 km^2, with extreme values of 4,286.412 km^2 in 2004 and 4,678.329 km^2 in 2024. LAI reached its minimum value of 0.391 in 2001 and maximum value of 0.522 in 2018, and overall increased slowly at a rate of 0.004 · a^-1. In contrast, solar radiation fluctuated downward at a rate of 0.153 MJ · m$^{-2 \cdot a}$-1, with the maximum and minimum values being 492.299 MJ · m^-2 in 2004 and 467.902 MJ · m^-2 in 2018, respectively.

Based on a dual machine-learning framework (RF and XGBoost), this study conducted a comparative analysis and systematically identified and quantitatively ranked the temporal influencing factors of the water-carbon variables NPP, ET, and WUE in the Qinghai Lake Basin from 2000 to 2024 (Figure 9). All models were run under a unified temporal scale and the same set of explanatory variables to ensure comparability of the results. For NPP, both RF and XGBoost identified LAI as the most important controlling factor, with feature importance values of 0.467 and 0.337, respectively, significantly higher than those of other variables. The next factor was water body area, with RF and XGBoost feature importance values of 0.183 and 0.231, respectively, indicating that lake expansion and wetland expansion have an important supporting role in vegetation productivity by regulating regional hydrothermal conditions and local microclimate. The contributions of temperature, wind speed, and precipitation were relatively weak, with feature importance values all below 0.15; the direct influence of solar radiation was the smallest. This result indicates that in the alpine lake basin, the canopy structure of vegetation controls the interception and acquisition capacity of photosynthetically active radiation and is the core mechanism driving interannual variation in NPP, while water availability plays a secondary regulatory role. The driving mechanisms of ET differed among different models. The RF results showed that LAI was the primary controlling factor for ET, with a feature importance of 0.451, followed by solar radiation at 0.180 and precipitation at 0.160, indicating that vegetation transpiration dominated changes in evapotranspiration on the annual scale. In comparison, XGBoost placed greater emphasis on the importance of precipitation, at 0.310, while LAI decreased to 0.280 and solar radiation was 0.229. This difference reflects the two models' different emphases regarding the formation mechanisms of ET: RF tends to capture long-term stable biological control effects, whereas XGBoost is more sensitive to nonlinear processes such as precipitation pulses and energy inputs. Overall, the synergistic effects of vegetation cover and water supply jointly shaped the interannual variation pattern of ET. Unlike NPP and ET, the model interpretability for WUE was significantly lower, suggesting that it is jointly controlled by multiple nonlinear processes and variable interactions. The RF results showed that precipitation was the most important driving factor of WUE, with a feature importance of 0.321, followed by temperature at 0.193 and water body area at 0.154. XGBoost identified water body area as the primary factor, with a feature importance of 0.432, followed by precipitation at 0.260, while the contributions of temperature and LAI were relatively limited.

3 Discussion

3.1 Spatiotemporal Evolution Patterns of Water-Carbon Variables

Over the past 25 years, NPP and ET in the Qinghai Lake Basin have continued to increase, consistent with the overall warming and wetting trend of the Qinghai-Tibet Plateau [33-34]. Vegetation growth in alpine regions is mainly limited by low temperature, and rising temperature is the core driving force for productivity improvement [35-36]. Increased precipitation alleviates drought stress and improves soil water content, and, together with warming, forms a synergistic effect that jointly promotes the sustained growth of NPP. The synchronous increase in ET is jointly driven by vegetation transpiration and land-surface evaporation. The increase in NPP, accompanied by greater LAI, leads to expansion of the transpiring surface area and enhanced vegetation transpiration [37], while rising temperature directly increases the potential for land-surface evaporation. In hydrologically relatively closed inland basins, enhanced ET means that more water vapor returns to the atmosphere rather than replenishing the lake; in the long term, this may affect the water level, water quality, and salinity of Qinghai Lake. The synchronous growth of NPP and ET indicates a high degree of process coordination between carbon sequestration and water consumption in alpine ecosystems. WUE, however, first decreased and then

Fig. 8 Interannual variations in factors influencing water and carbon variables across different time scales in the Qinghai Lake Basin. Panels: (a) air temperature; (b) precipitation; (c) wind speed; (d) water-body area; (e) LAI; (f) solar radiation.

Figure 2: Fig. 8 Interannual variations in factors influencing water and carbon variables across different time scales in the Qinghai Lake Basin. Panels: (a) air temperature; (b) precipitation; (c) wind speed; (d) water-body area; (e) LAI; (f) solar radiation.

increased, with 2017 as the turning point.

Fig. 8 Interannual variations in factors influencing water and carbon variables across different time scales in the Qinghai Lake Basin

···increased, reflecting the transformation of the ecosystem from passive response to active adaptation. In the early stage, accelerated warming led to a decline in WUE through increased ET; in the later stage, when temperature approached the evaporation threshold, the growth rate of ET was suppressed[^38]. Meanwhile, the accumulation of LAI and the expansion of water bodies jointly improved carbon-fixation efficiency, together promoting the rebound of WUE. Spatially, NPP and WUE showed a pattern of being high in the southeast and low in the northwest, whereas ET showed a pattern of being high in the north and low in the south. The differences in their spatial patterns indicate significant spatial differentiation in water–carbon processes within the basin, and this differentiation is closely related to the spatial allocation of elevation, vegetation type, and local climatic conditions[^39–^40].

3.2 Analysis of influencing factors at spatial and temporal scales

At the spatial scale, NPP and WUE decreased significantly with increasing elevation, with the decline being especially evident in the 3600–3900 m interval. This is related to environmental stresses such as lower temperatures and shortened growing seasons at higher elevations[^37]; ET, however, showed no significant association with elevation[^41]. Vegetation type is an important factor affecting the spatial differentiation of NPP and WUE. Marshes had the highest values, followed by cultivated vegetation, while grasslands and thickets were also relatively high, and meadows, deserts, and alpine vegetation were relatively low. The high values in marshes benefited from perennial water accumulation and high nutrient conditions in wetlands[^42], while cultivated ···

Fig. 9 Characteristic importance of factors influencing water and carbon variables in the Qinghai Lake Basin across different time scales

Vegetation is related to human management[^43], while grasslands and shrublands are associated with adaptability in photosynthetic capacity and water regulation[^44]. It is worth noting that swamps stand out in the carbon sink and water-use capacity of the Qinghai Lake Basin, whereas in other basins,

Fig. 9 Characteristic importance of factors influencing water and carbon variables in the Qinghai Lake Basin across different time scales. Panels: (a) NPP; (b) ET; (c) WUE. Legends: RF and XGBoost. Axes: feature importance; time-series influencing factors including air temperature, precipitation, wind speed, water-body area, LAI, and solar radiation.

Figure 3: Fig. 9 Characteristic importance of factors influencing water and carbon variables in the Qinghai Lake Basin across different time scales. Panels: (a) NPP; (b) ET; (c) WUE. Legends: RF and XGBoost. Axes: feature importance; time-series influencing factors including air temperature, precipitation, wind speed, water-body area, LAI, and solar radiation.

the water-use efficiency of shrublands, grasslands, and cultivated vegetation is higher, and that of swamps is relatively low[^45]. This indicates that the hydrological and carbon characteristics of vegetation are regulated by multiple factors such as topography and climate, and exhibit obvious spatial heterogeneity. Partial correlation analysis further shows that NPP is mainly positively driven by air temperature and LAI, and negatively constrained by solar radiation; ET is jointly regulated by LAI, air temperature, and precipitation; WUE is significantly negatively correlated with precipitation, while LAI is positively correlated only in the peripheral areas of the basin. The spatial differences in the responses of these variables confirm that vegetation type and LAI are core elements in resolving the spatial differentiation of the water–carbon cycle[^46].

At the temporal scale, the variable-importance analysis of RF and XGBoost shows that LAI is the primary driver of NPP (0.467 for RF and 0.337 for XGBoost), followed by water-body area, while air temperature, precipitation, and wind speed contribute relatively weakly. This indicates that the canopy structure of vegetation dominates interannual fluctuations in NPP, and that lakes and wetland expansion play an important supporting role[^47]. For ET, RF ranks LAI first, whereas XGBoost ranks precipitation first. The difference arises because the former emphasizes long-term stable biological control effects, while the latter is more sensitive to nonlinear processes such as precipitation pulses[^47]. Solar radiation is identified as an important factor in both models, indicating that ET is jointly regulated by vegetation transpiration, water supply, and energy conditions. The explanatory power of the WUE models is relatively low, reflecting its composite nature as the ratio of NPP to ET: RF identifies precipitation as the primary factor (0.321), whereas XGBoost places greater emphasis on water-body area (0.432), consistent with observations that the latter expands significantly together with water-body area. These results support the inference that increased precipitation in the early period led to a decline in WUE through ET, while in the later period water-body expansion and air temperature approaching a threshold suppressed the growth rate of ET, and increased LAI promoted carbon uptake, jointly driving the rebound of WUE. The ranking differences between the two models originate from their algorithmic principles: RF is based on the Bagging framework and emphasizes the stable contribution of variables[^48], whereas XGBoost is based on the Boosting concept and has stronger characterization of nonlinear relationships and threshold effects[^49]. In addition, the relatively low explanatory power of the WUE model may also be related to the fact that some key variables have not yet been incorporated, such as soil moisture, freeze–thaw processes, and the intensity of human activities. The absence of these variables may limit the explanatory capability of the model. In the future, more refined ecophysiological parameters should be introduced, more indicators should be incorporated, and advanced model frameworks should be explored, while treating the interpretation of WUE predictions cautiously, so as to comprehensively reveal its regulatory mechanisms[^50].

3.3 Transverse comparison with typical basins on the Qinghai–Tibet Plateau

This study conducts a transverse comparison between the Qinghai Lake Basin and other typical basins on the Qinghai–Tibet Plateau. The water and carbon variables show obvious spatial differentiation. In terms of NPP, the Sanjiangyuan region and the Huangshui River Basin likewise exhibit a spatial pattern of "high in the southeast and low in the northwest," and their growth rates (2.00 $g \cdot C \cdot m^{-2} \cdot a^{-1}$ and 2.83 $g \cdot C \cdot m^{-2} \cdot a^{-1}$, respectively) are close to that of the Qinghai Lake Basin (2.511 $g \cdot C \cdot m^{-2} \cdot a^{-1}$)[^51-^52]. The spatial characteristics of ET, however, show certain differences. As a typical endorheic basin, the Qinghai Lake Basin has a relatively closed water cycle[^53] and presents a pattern of "high in the north and low in the south"; whereas in the Sanjiangyuan region, Zoige Wetland, and the Yarlung Zangbo River Basin, ET also shows an increasing trend over time.

…trend, but because it is an endorheic river system and the river network is mostly oriented east-west, the ET spatial pattern correspondingly shows an "east-high, west-low" distribution[6]. As a water–carbon coupling variable, WUE has shown nonlinear changes over the past nearly 25 years in the Qinghai Lake Basin. In recent years, similar characteristics have also appeared in areas such as Zoige Wetland and the Three-River Headwaters Region; however, under the overall pattern of "higher in the southeast and lower in the northwest," the WUE in these regions—1.03 g C · m$^{-2 \cdot \mathrm{mm}}$-1 and 0.59 g C · m$^{-2 \cdot \mathrm{mm}}$-1, respectively—is higher than that of the Qinghai Lake Basin (0.53 g C · m$^{-2 \cdot \mathrm{mm}}$-1)[7].

Because each basin has its own spatial heterogeneity and the indicators selected in different studies are not entirely the same, there are differences in the interpretation of changes in water–carbon variables. Nevertheless, horizontal comparison can still provide a reference for understanding the relative importance of influencing factors. The significant increase in NPP driven by warming has likewise been confirmed in the Three-River Headwaters Region, the Tarim River Basin, and the upper Yangtze River Basin. In recent years, the influence of air temperature on NPP has generally been greater than that of water factors such

[6] References 54–56 cited on this page but not visible here.
[7] References 57–58 cited on this page but not visible here.

as precipitation across the Qinghai–Tibet Plateau; warming-induced vegetation growth has become a common pattern in non-forest ecosystems on the Qinghai–Tibet Plateau[8]. The results of this study indicate that LAI and precipitation are the dominant drivers of ET change in the Qinghai Lake Basin, whereas related studies show that the main factor affecting ET in the upper Yellow River and the Yarlung Zangbo River is LAI, while that in the upper Jinsha River is mainly precipitation[9]. Differences in the dominant factors of ET among different basins reflect their integrated response mechanisms to the natural environment. Owing to the relatively large lake area and distinctive water-circulation environment in the Qinghai Lake Basin, WUE is more sensitive to water factors such as water-body area and precipitation than in other basins; in areas such as Zoige Wetland and the Yellow River source region, however, the dominant factor of WUE remains LAI[10]. This particularity further reflects the difficulty of explaining WUE in the Qinghai Lake Basin using a single variable.

4 Conclusion

(1) Over the past nearly 25 years, both NPP and ET have shown significant upward trends, while WUE first decreased and then increased with 2017 as the inflection point, reflecting a staged adjustment in the water–carbon coupling process from an early period dominated by evaporative water consumption to a later period dominated by synergistic water–carbon enhancement. Spatially, NPP and WUE exhibit a pattern of "higher in the southeast and lower in the northwest," whereas ET shows a pattern of "higher in the north and lower in the south." Elevation and vegetation type are the dominant factors controlling spatial differentiation.

(2) In terms of influencing factors, at the spatial scale, air temperature and LAI positively drive NPP; precipitation and air temperature jointly regulate ET; and WUE is significantly negatively correlated with precipitation. Rising elevation significantly suppresses NPP and WUE, while marshes, cultivated vegetation, grasslands, and shrublands have higher carbon-sequestration efficiency and water-use capacity.

(3) At the temporal scale, LAI is the core driving factor of NPP (RF feature importance: 0.467; XGBoost: 0.337). ET is jointly regulated by LAI and precipitation, while WUE is highly sensitive to moisture conditions (precipitation and water-body area). The two machine-learning methods effectively identified nonlinear driving relationships, providing methodological references for research on water–carbon coupling in alpine basins.

References

[1] Gentine P, Green J, Guérin M, et al. Coupling between the terrestrial car-

[8] Reference 59 cited on this page but not visible here.
[9] References 60-61 cited on this page but not visible here.
[10] References 57-58 cited on this page but not visible here.

bon and water cycles: A review[J]. Iop Publishing, 2019, 14(8): 083003, doi: 10.1088/1748-9326/ab22d6.

[2] Huang Richao, Chen Xi, Sun Yimeng, et al. Validation of watershed soil effective depth based on water balance and its effect on simulation of land surface water-carbon flux[J]. Acta Geographica Sinica, 2016, 71(5): 807-816. [Huang Richao, Chen Xi, Sun Yimeng, et al. Validation of watershed soil effective depth based on water balance and its effect on simulation of land surface water-carbon flux[J]. Acta Geographica Sinica, 2016, 71(5): 807-816.]

[3] Duan Kai, Sun Ge, Liu Ning. A review of research on watershed water-carbon balance evolution in a changing environment[J]. Journal of Hydraulic Engineering, 2021, 52(3): 300-309. [Duan Kai, Sun Ge, Liu Ning. A review of research on watershed water-carbon balance evolution in a changing environment[J]. Journal of Hydraulic Engineering, 2021, 52(3): 300-309.]

[4] Lü Meixia, Ma Zhuguo, Li Mingxing. A review on the changing water cycle of the Yellow River Basin under changes in climate, vegetation, and human water use[J]. Transactions of Atmospheric Sciences, 2023, 46(6): 801-812. [Lü Meixia, Ma Zhuguo, Li Mingxing. A review on the changing water cycle of the Yellow River Basin under changes in climate, vegetation, and human water use[J]. Transactions of Atmospheric Sciences, 2023, 46(6): 801-812.]

[5] Wang Xuanyu, Gu Wenquan, Hu Yajie, et al. Response law of water cycle elements in the Hanjiang River Basin under changing environment[J]. China Rural Water and Hydropower, 2024(7): 35-44. [Wang Xuanyu, Gu Wenquan, Hu Yajie, et al. Response law of water cycle elements in Hanjiang River Basin under changing environment[J]. China Rural Water and Hydropower, 2024(7): 35-44.]

[6] Tong Kai, Ju Qin, Zhao Yinjun, et al. Assessment of actual evapotranspiration in the Xijiang River Basin based on water balance[J]. Geographical Science, 2025, 45(4): 910-918. [Tong Kai, Ju Qin, Zhao Yinjun, et al. Assessment of actual evapotranspiration in the Xijiang River Basin based on water balance[J]. Geographical Science, 2025, 45(4): 910-918.]

[7] Wang T. Dynamic changes of net primary productivity and its response to temperature and precipitation in China[J]. Iop Publishing, 2018, 186: 012044, doi: 10.1088/1755-1315/186/6/012044.

[8] Zhang Liankai, Qin Xiaoqun, Yang Hui, et al. Transported fluxes of the riverine carbon and seasonal variation in Pearl River Basin[J]. Environmental Science, 2013, 34(8): 3025-3034. [Zhang Liankai, Qin Xiaoqun, Yang Hui, et al. Transported fluxes of the riverine carbon and seasonal variation in Pearl River Basin[J]. Environmental Science, 2013, 34(8): 3025-3034.]

[9] Wang Chenlu, Yu Zhongbo, Liu Di, et al. Impact of vegetation change at Yellow River Basin on local water-carbon interaction[J]. Water Resources and Power, 2022, 40(1): 150-154. [Wang Chenlu, Yu Zhongbo, Liu Di, et al. Impact

of vegetation change at Yellow River Basin on local water-carbon interaction[J]. Water Resources and Power, 2022, 40(1): 150-154.]

[10] Gong Li, Liang Kang, Liu Changming. Spatiotemporal variation characteristics of water-carbon variables and their influencing factors in the water-source conservation area of the Yellow River[J]. Progress in Geography, 2023, 42(9): 1677-1690. [Gong

Li, Liang Kang, Liu Changming. Spatial and temporal variation characteristics of the water and carbon variables in the water conservation zone of the Yellow River and their influencing factors[J]. Progress in Geography, 2023, 42(9): 1677-1690.]

[11] He Ping, Liu Yankun, Chen Yao, et al. Spatiotemporal patterns and influencing factors of vegetation NPP in Heilongjiang Province[J]. Environmental Ecology, 2024, 6(11): 19-29, 36. [He Ping, Liu Yankun, Chen Yao, et al. Spatiotemporal patterns and influencing factors of vegetation NPP in Heilongjiang Province[J]. Environmental Ecology, 2024, 6(11): 19-29, 36.]

[12] Zhou Nafang, Gong Enjun, Bai Tianhao, et al. Analysis of temporal and spatial dynamics and its influencing factors of NPP in Qinba Mountain Area based on the CASA model[J]. Acta Ecologica Sinica, 2025, 45(4): 1829-1843. [Zhou Nafang, Gong Enjun, Bai Tianhao, et al. Analysis of temporal and spatial dynamics and its influencing factors of NPP in Qinba Mountain Area based on the CASA model[J]. Acta Ecologica Sinica, 2025, 45(4): 1829-1843.]

[13] Wang Qi, Zhang Runrun. Spatial and temporal variation characteristics of surface evapotranspiration in the Yarlung Zangbo River Basin and its influencing factors[J]. Water Resources and Power, 2025, 43(5): 34-38. [Wang Qi, Zhang Runrun. Spatial and temporal variation characteristics of surface evapotranspiration in the Yarlung Zangbo River Basin and its influencing factors[J]. Water Resources and Power, 2025, 43(5): 34-38.]

[14] Lu Han, Zeng Yongnian, Wang Pancheng. Spatiotemporal variation of actual evapotranspiration and its influencing factors in the northeast Qinghai-Tibet Plateau[J]. Arid Land Geography, 2025, 48(5): 753-764. [Lu Han, Zeng Yongnian, Wang Pancheng. Spatiotemporal variation of actual evapotranspiration and its influencing factors in the northeast Qinghai-Tibet Plateau[J]. Arid Land Geography, 2025, 48(5): 753-764.]

[15] Wang Renjun, Liu Baokang, Du Yu'e, et al. Extraction method and accuracy evaluation of typical lake water body in Hoh Xil region based on GF-6 WFV data[J]. Bulletin of Surveying and Mapping, 2022, 542(5): 32-37. [Wang Renjun, Liu Baokang, Du Yu' e, et al. Extraction method and accuracy evaluation of typical lake water body in Hoh Xil region based on GF-6 WFV data[J]. Bulletin of Surveying and Mapping, 2022, 542(5): 32-37.]

[16] Yu Bohua, Lü Changhe, Lü Tingting, et al. Regional differentiation of vegetation change in the Qinghai-Tibet Plateau[J]. Progress in Geography, 2009,

28(3): 391-397. [Yu Bohua, Lü Changhe, Lü Tingting, et al. Regional differentiation of vegetation change in the Qinghai-Tibet Plateau[J]. Progress in Geography, 2009, 28(3): 391-397.]

[17] Zheng Zhoutao, Zhang Yangjian. Variation in ecosystem water use efficiency and its attribution analysis during 1982-2018 in Qingzang Plateau[J]. Chinese Journal of Plant Ecology, 2022, 46(12): 1486-1496. [Zheng Zhoutao, Zhang Yangjian. Variation in ecosystem water use efficiency and its attribution analysis during 1982-2018 in Qingzang Plateau[J]. Chinese Journal of Plant Ecology, 2022, 46(12): 1486-1496.]

[18] Wang Xiaohui, Zhang Liang, Li Junqing, et al. Study on XGBoost improved method based on genetic algorithm and random forest[J]. Computer Science, 2020, 47(Suppl. 2): 454-458, 463. [Wang Xiaohui, Zhang Liang, Li Junqing, et al. Study on XGBoost improved method based on genetic algorithm and random forest[J]. Computer Science, 2020, 47(Suppl. 2): 454-458, 463.]

[19] Li Hui, Liu Tiejun, Wang Shaohui, et al. Spatial and temporal variation of water use efficiency and its influencing factors in desert steppe of Inner Mongolia from 2001 to 2021[J]. Arid Land Geography, 2024, 47(6): 993-1003. [Li Hui, Liu Tiejun, Wang Shaohui, et al. Spatial and temporal variation of water use efficiency and its influencing factors in desert steppe of Inner Mongolia from 2001 to 2021[J]. Arid Land Geography, 2024, 47(6): 993-1003.]

[20] Zhou Zuhao, Liu Jiajia, Yan Ziqi, et al. Attribution analysis of the natural runoff evolution in the Yellow River Basin[J]. Advances in Water Science, 2022, 33(1): 27-37. [Zhou Zuhao, Liu Jiajia, Yan Ziqi, et al. Attribution analysis of the natural runoff evolution in the Yellow River Basin[J]. Advances in Water Science, 2022, 33(1): 27-37.]

[21] Ye Qun, Lai Chenxi, Xiao Jing, et al. Spatiotemporal variation characteristics of Poyang Lake water area based on Sentinel-1 satellite[J]. Jiangxi Cehui, 2024(4): 1-4. [Ye Qun, Lai Chenxi, Xiao Jing, et al. Spatiotemporal variation characteristics of Poyang Lake water area based on Sentinel-1 satellite[J]. Jiangxi Cehui, 2024(4): 1-4.]

[22] Zhou Meilin, Liu Jiahong, Liu Xisheng, et al. Analysis of driving forces and spatial scale effects on vegetation dynamics in the Qinghai Lake Basin[J]. China Environmental Science, 2024, 44(3): 1497-1506. [Zhou Meilin, Liu Jiahong, Liu Xisheng, et al. Analysis of driving forces and spatial scale effects on vegetation dynamics in the Qinghai Lake Basin[J]. China Environmental Science, 2024, 44(3): 1497-1506.]

[23] McFEETERS S K. The use of the normalized difference water index (NDWI) in the delineation of open water features[J]. International Journal of Remote Sensing, 1996, 17(7): 1425-1432.

[24] Sen K P. Estimates of the regression coefficient based on Kendall' s Tau[J]. Journal of the American Statistical Association, 1968, 63(324): 1379-1389.

[25] Hernández G O, García V L. False discovery rate estimation and control in remote sensing: Reliable statistical significance in spatially dependent gridded data[J]. Remote Sensing Letters, 2025, 16(5): 537-548.

[26] Heumann W B. The multiple comparison problem in empirical remote sensing[J]. Photogrammetric Engineering & Remote Sensing, 2015, 81(12): 921-926.

[27] Yang Fule, Rong Yanshu, Yang Fuguang. Analysis of pan evaporation change trend and its influencing factors in Sichuan Basin[J]. Water Resources Protection, 2014, 30(3): 38-45. [Yang Fule, Rong Yanshu, Yang Fuguang. Analysis of pan evaporation change trend and its influencing factors in Sichuan Basin[J]. Water Resources Protection, 2014, 30(3): 38-45.]

[28] Yu Ting, Zhang Yinyin, Zhang Ruizhi, et al. Distribution ratio prediction of major components in 30%TBP/kerosene-HNO_3 system based on machine learning[J]. Atomic Energy Science and Technology, 2025, 59(1): 14-23. [Yu Ting, Zhang Yinyin, Zhang Ruizhi, et al. Distribution ratio prediction of major components in 30%TBP/kerosene-HNO_3 system based on machine learning[J]. Atomic Energy Science and Technology, 2025, 59(1): 14-23.]

[29] Yang L J, Zhu Q Y, Ge X C, et al. Transmit antenna selection for Millimeter-WaveMIMO system based on GBDT[J]. Institute of Electrical and Electronics Engineers (ieee), 2023, 8(1): 71-79.

[30] Hajihosseinlou M, Maghsoudi A, Ghezelbash R. A novel scheme for mapping of MVT-type Pb-Zn prospectivity: LightGBM, a highly efficient gradient boosting decision tree machine learning algorithm[J]. Natural Resources Research, 2023, 32(6): 2417-2438.

[31] Zeng Shuyu, Xie Tao, Kong Ruiyao. Water depth inversion based on a CatBoost-XGBoost combined model[J]. Hydrographic Surveying and Charting, 2023, 43(3): 59-63.

[32] Fan Haiwei, Shi Shuang, Zhang Bomin, et al. Improved learning resource recommendation algorithm of deep neural network based on MLP[J]. Application Research of Computers, 2020, 37(9): 2629-2633.

[33] Han Yizhe, Liao Jie, Zhao Yifei, et al. Multi-sphere observation network and climate warming and humidification research on the Qinghai-Xizang Plateau: Advances and future directions[J]. Plateau Meteorology, 2026, 45(2): 305-323.

[34] Han Dandan, Mu Xingmin, Gao Peng, et al. Dynamic changes of vegetation in Loess Plateau and its response to extreme climate[J]. Bulletin of Soil and Water Conservation, 2020, 40(2): 247-254.

[35] Chen Jiangbo, Zhao Yuanyuan, Ding Guodong, et al. Changes in normalized difference vegetation index in the Yarlung Tsangpo River Basin and its response to climatic factors[J]. Chinese Journal of Applied Ecology, 2025, 36(9): 2797-2804.

[36] Ma M M, Qu Y P, Lü J, et al. The 2022 extreme drought in the Yangtze River Basin: Characteristics, causes and response strategies[J]. River, 2022, 1(2): 162–171.

[37] Lai Ming, Chen Rensheng, Liu Jiufen, et al. Temporal and spatial evolution of water yield in the lower reaches of the Yarlung Zangbo River and its response to climate and land use change[J]. Pratacultural Science, 2022, 39(12): 2516–2526.

[38] Jiang Cuihong, Li Guangyong, Cheng Tao, et al. Spatial-temporal pattern variation and impact factors of ecosystem service values in the Qinghai Lake Watershed[J]. Resources Science, 2016, 38(8): 1572–1584.

[39] Ding Chenshen, Cao Shengkui, Zhang Fuling, et al. Spatial patterns and modeling of soil moisture in the Qinghai Lake Basin[J]. Acta Agrestia Sinica, 2026, 34(3): 984–997.

[40] Liu Xiaoli. Decipher soil organic carbon dynamics and driving forces in the Loess Plateau using machine learning[D]. Zhengzhou: Zhengzhou University, 2024.

[41] Ma Lu. The study of extreme climate influence on unsaturated soil physical and mechanical properties in Chongqing area[D]. Chongqing: Chongqing Jiaotong University, 2015.

[42] Gao Xin, Wang Hui, Li Guoshuang, et al. Discussion on wetland carbon sink function: A case study of peatlands and marsh wetlands[J]. Agricultural Science and Engineering in China, 2018, 30(6): 20–21.

[43] Shang Siliang, Chen Guopeng, Yang Yonghong, et al. High-precision identification of frost mounds and multi-scale spatial aggregation mechanisms via synergistic UAV multi-source data and machine learning: A case study of Meiren Grassland[J]. Acta Ecologica Sinica, 2026, 46(1): 105–121.

[44] Fan Zhiqing. Deep learning-based assessment research on Yellow River Basin[J]. Energy and Energy Conservation, 2025(Suppl. 1): 150–153.

[45] Liu Chan, Liu Bing, Zhao Wenzhi, et al. Temporal and spatial variability of water use efficiency of vegetation and its response to precipitation and temperature in Heihe River Basin[J]. Acta Ecologica Sinica, 2020, 40(3): 888–899.

[46] Liu Xinyi. Spatiotemporal variations and driving mechanisms of water use efficiency in typical ecosystems of the Mongolian Plateau[D]. Hohhot: Inner Mongolia Normal University, 2024.

[47] Guo Boyu, Jin Xin, Jin Yanxiang, et al. Understanding the drivers of vegetation change in alpine and arid regions using machine learning: Contributions of climate change and human activities[J]. Chinese Journal of Applied Ecology, 2026, 46(8): 1–15.

[48] Breiman L. Random forests[J]. Machine Learning, 2001, 45(1): 5–32.

[49] Chen T, Guestrin C. XGBoost: A scalable tree boosting system[C]// Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. New York: ACM, 2016: 785-794.

[50] Li Xia, Wang Xiaokang, Liu Xiuhua, et al. Detection of spatiotemporal changes in vegetation NDVI and climatic factors in Shaanxi Province from 2000 to 2020[J]. Research of Soil and Water Conservation, 2024, 31(2): 443-453. [Li Xia, Wang Xiaokang, Liu Xiuhua, et al. Spatiotemporal variation of vegetation NDVI and climate factor detection in Shaanxi Province from 2000–2020[J]. Research of Soil and Water Conservation, 2024, 31(2): 443-453.]

[51] Zuo Chan, Wang Junbang, Zhang Xiujuan, et al. Trends in vegetation net primary productivity and influencing factors in Sanjiangyuan National Park[J]. Acta Ecologica Sinica, 2022, 42(14): 5559-5573. [Zuo Chan, Wang Junbang, Zhang Xiujuan, et al. Changes and influencing factors of vegetation net primary productivity in the Sanjiangyuan National Park[J]. Acta Ecologica Sinica, 2022, 42(14): 5559-5573.]

[52] Ma Daoming, Liu Dayang, Qi Yuanjing, et al. Spatiotemporal evolution characteristics of vegetation net primary productivity in the Huangshui River Basin and its driving factors[J/OL]. Acta Ecologica Sinica. [2026-05-14]. https://doi.org/10.20103/j.stxb.202512293515. [Ma Daoming, Liu Dayang, Qi Yuanjing, et al. Spatiotemporal dynamics and driving factors of vegetation NPP in Huangshui River Basin[J/OL]. Acta Ecologica Sinica. [2026-05-14]. https://doi.org/10.20103/j.stxb.202512293515.]

[53] Wu G X, Zhou X J, Xu X D, et al. An integrated research plan for the Tibetan Plateau land-air coupled system and its impacts on the global climate[J]. Bulletin of the American Meteorological Society, 2023, 104(1): 158-177.

[54] Jiang Yao, Xia Zihao, Xiong Lüyang, et al. Spatiotemporal evolution of water-cycle elements and runoff-driving factors in the Yarlung Zangbo River Basin[J]. Journal of Soil and Water Conservation, 2026, 40(1): 25-33. [Jiang Yao, Xia Zihao, Xiong Lüyang, et al. Spatiotemporal evolution of water cycle components and runoff driving factors in Yarlung Zangbo River Basin[J]. Journal of Soil and Water Conservation, 2026, 40(1): 25-33.]

[55] Chen Weiyao, Sun Yang, Xin Penglei. Spatiotemporal variation characteristics and influencing factors of evapotranspiration in the Three-River Headwaters Region[J]. Express Water Resources & Hydropower Information, 2024, 45(1): 6-11. [Chen Weiyao, Sun Yang, Xin Penglei. Spatial-temporal variation characteristics and influencing factors of evapotranspiration in Three-River Headwaters Region[J]. Express Water Resources & Hydropower Information, 2024, 45(1): 6-11.]

[56] Qi Dongmei, Li Yueqing, Zhou Changyan, et al. Variation characteristics of runoff and its influencing factors in the Zoige Wetland region[J]. Journal of Glaciology and Geocryology, 2025, 47(1): 14-29. [Qi Dongmei, Li Yueqing, Zhou Changyan, et al. Variation characteristics of runoff and its influencing factors in

Zoige Wetland[J]. Journal of Glaciology and Geocryology, 2025, 47(1): 14-29.]

[57] Jing Juanli, Qin Shiping, Wang Yongfeng, et al. Spatiotemporal evolution and driving mechanism of vegetation water-use efficiency in southwest China[J]. Water Resources Protection, 2026, 42(2): 89-99. [Jing Juanli, Qin Shiping, Wang Yongfeng, et al. Spatiotemporal evolution and driving mechanism of vegetation water use efficiency in southwest China[J]. Water Resources Protection, 2026, 42(2): 89-99.]

[58] Ma Ning. Spatiotemporal changes and driving factors of ecosystem water-use efficiency across the headwater region of the eastern Tibetan Plateau[J]. Acta Geographica Sinica, 2025, 80(7): 1937-1953. [Ma Ning. Spatial-temporal changes in the ecosystem water use efficiency across the headwater region of eastern Tibetan Plateau and the drivers[J]. Acta Geographica Sinica, 2025, 80(7): 1937-1953.]

[59] Liu X, Tian K J, Chao N F, et al. Analysis of spatial and temporal variations of vegetation NPP and TWS in the Yangtze River Basin[J]. Scientific Reports, 2024, 14(1): 24908, doi: 10.1038/S41598-024-75447-5.

[60] Wen Xinzhu, Yin Zhenliang, Zhu Rui, et al. Spatiotemporal variation characteristics and influencing factors of water-carbon variables in the Yellow River Basin[J]. Acta Ecologica Sinica, 2025, 45(18): 9278-9293. [Wen Xinzhu, Yin Zhenliang, Zhu Rui, et al. The spatiotemporal variation characteristics and influencing factors of water carbon variables in the Yellow River Basin[J]. Acta Ecologica Sinica, 2025, 45(18): 9278-9293.]

[61] Wang L L, Wang Z G, Liu C M, et al. A flexible framework hydrolinformatic modeling system—HIMS[J]. Water, 2018, 10(7): 962, doi: 10.3390/w10070962.

Spatiotemporal changes and influencing factors of water and carbon variables in the Qinghai Lake Basin over the past 25 years

YAN Pengxu,^1, ZHANG Lihua,^1,2 ZENG Fanxing,^3 BAI Xiaohui,^1, YE Yang,^1 CAO Yijie^1

(1. College of Geography and Environmental Science, Northwest Normal University, Lanzhou 730070, Gansu, China;
2. Key Laboratory of Resource Environment and Sustainable Development of Oasis, Lanzhou 730070, Gansu, China;
3. Maynooth International Engineering College, Fuzhou University, Fuzhou 350108, Fujian, China)

Abstract: The Qinghai-Xizang Plateau is an area sensitive to global climate change, and the Qinghai Lake Basin, along its northeastern edge, serves as a typical alpine inland river basin. Studying the water-carbon coupling mechanism is of great significance for revealing the laws of carbon-water interaction in alpine ecosystems and supporting the coordinated management of regional water resources and carbon sinks. Based on multi-source remote sensing and meteorological data from 2000 to 2024, and using net primary productivity (NPP), evapotranspiration (ET) and water use efficiency (WUE) as core variables, this study systematically analyzes their spatiotemporal change characteristics. It integrates random forest and XGBoost machine learning methods to analyze the driving mechanisms from two dimensions: Space (altitude, vegetation type, meteorological factors, leaf area index) and time (meteorological factors, leaf area index, water area). The results show that: (1) NPP and ET in the Qinghai Lake Basin have shown a significant upward trend over the past 25 years (growth rates of 2.511 g C ·m^−2 a^−1 and 4.470 mm ·a^−1, respectively), WUE has shown a nonlinear change pattern, first declining and then rising, with 2017 as a turning point. (2) Spatially, NPP and WUE showed a pattern of "high in the southeast and low in the northwest", whereas ET showed one of "high in the north and low in the south", demonstrating significant spatial heterogeneity. (3) On a spatial scale, altitude significantly influences the spatial variabilities of NPP and WUE but has no significant effect on ET. Vegetation type dominates the spatial differences in NPP and WUE, with marshes, cultivated vegetation, grassland, and scrubland showing higher carbon sequestration capacity and water use efficiency. Among meteorological factors, temperature and leaf area index show a significant positive effect on NPP, whereas precipitation and temperature jointly regulate ET. WUE shows a significant negative correlation with precipitation. (4) On a temporal scale, LAI is a core driver of NPP changes (RF importance 0.467, XGBoost 0.337). ET was jointly regulated by leaf area index and precipitation. WUE is more sensitive to water conditions (precipitation, water area), and the model's interpretability is significantly higher than that of single water and carbon variables. This study reveals the multi-scale driving laws of water-carbon coupling in alpine inland river basins, thus providing a scientific basis for ecological protection and comprehensive management of water-carbon resources in the Qinghai-Xizang Plateau.

Keywords: Qinghai Lake Basin; water-carbon coupling; net primary productivity; evapotranspiration; water use efficiency