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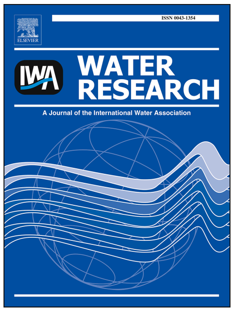

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PII: S0043-1354(20)30555-8

DOI: https://doi.org/10.1016/j.watres.2020.116018

Reference: WR 116018

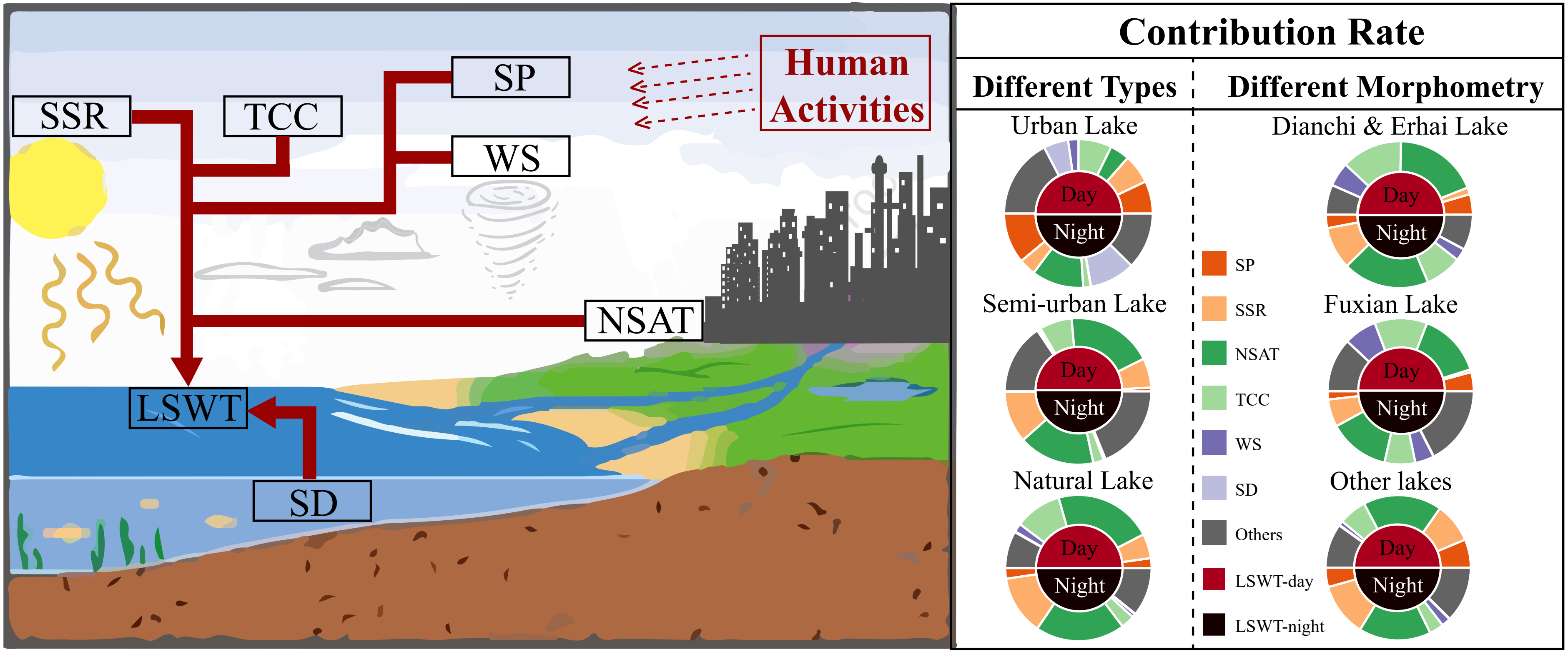
To appear in: *Water Research*

Received Date: 2 March 2020

Revised Date: 27 May 2020

Accepted Date: 4 June 2020

Please cite this article as: Yang, K., Yu, Z., Luo, Y., Analysis on driving factors of lake surface water temperature for major lakes in Yunnan-Guizhou Plateau, *Water Research* (2020), doi: https://doi.org/10.1016/j.watres.2020.116018.



SSR
TCC
SP
WS
Human Activities
NSAT
LSWT
SD
Contribution Rate
Different Types
Different Morphometry
Urban Lake
Semi-urban Lake
Natural Lake
Dianchi & Erhai Lake
Fuxian Lake
Other lakes
Day
Night
SP
SSR
NSAT
TCC
WS
SD
Others
LSWT-day
LSWT-night

Analysis on Driving Factors of Lake Surface Water Temperature for Major Lakes in Yunnan-Guizhou Plateau

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Abstract: Lake surface water temperature (LSWT) is an important factor in lake ecological environments. It has been observed that LSWT have followed an upward trend in the last half century, which has had serious impacts on regional biodiversity and climate. It is important to understand the main reason for this phenomenon in order to have a basis for controlling and improving the regional ecological environment. In this study, the contribution rates of near surface air temperature (NSAT), surface pressure (SP), surface solar radiation (SSR), total cloud cover (TCC), wind speed (WS) and Secchi depth (SD) to LSWT of 11 naturally formed lakes in the Yunnan-Guizhou Plateau are quantified. The characteristics of and relationships between the various factors and LSWT in lakes of different types and attributes are revealed. The results show that: (1) from 2001 to 2018, most lakes were warming; the change rate of LSWT-day was higher than that of LSWT-night. The mean comprehensive warming rate (MCWR) of LSWT-day was 0.42 ℃/decade, and the mean comprehensive change rate (MCCR) was 0.31 ℃/decade; the MCWR of LSWT-night was 0.19 ℃/decade, and the MCCR was 0.01 ℃/decade. NSAT and SSR were most strongly correlated with LSWT-day/night. There were no large seasonal differences in the correlation between NSAT and LSWT-day, while seasonal differences in the correlations between NSAT with LSWT-night and SSR with LSWT-day/night were observed. (2) NSAT and SSR were the most important factors affecting LSWT-day/night changes, with contribution rates of 30.24% and 44.34%, respectively. LSWT-day was more affected by SP and SSR in small, shallow, and low-storage lakes. For larger lakes, LSWT-day was more affected by WS, while LSWT-night was greatly affected by TCC. Urban and semi-urban lakes were more affected by SSR and NSAT; for natural lakes, the decreasing SD affected the increases in LSWT, which indirectly reflects the impact of human activities. LSWT-day/night responded differently to different morphological characteristics of the lakes and different intensities of human activity.

Keywords: Lake surface water temperature; Plateau lake; Yunnan Guizhou Plateau; Driving factor; Contribution rate

1 Introduction

Lakes are important ecological resources. The ecological environment of lake is not only associated with the quality of the regional ecological environment but also the sustainable development of cities (Dokulil, 2014; Zhang et al., 2015). It can also reflect the status of the regional environment (Dokulil., 2014). Water temperature is a basic physical property and an important environmental condition. It affects the metabolism of organisms living in the lake as well as the decomposition of organic materials, and determines the primary productivity of lakes (Sharma et al., 2007). Lake surface water temperature (LSWT) can directly reflect the material and energy exchange processes of the water-land-atmosphere system, and can also serve as an indicator of climate change and human activities (Yang et al., 2019; He et al., 2019; Weber et al., 2018; O'Reilly, 2015; Zhang et al., 2016). Changes in the LSWT would have a dynamic and complex fatal impact on the physical, biological, and chemical processes occurring in the lake ecological environment (Adrian et al., 2009; O'Reilly et al., 2015). In the past 30 years, the LSWTs of most lakes around the world have risen rapidly at an average rate of 0.34 □/decade, which could lead to ecological problems such as the prolongation of the cyanobacteria suitable growth period and the aggravation of eutrophication, environmental problems such as the prolongation of the lake thermal stratification period, the increase of thermocline depth and strength, and hypoxia at the bottom of lakes with increased(O'Reilly., 2015).

The rise in LSWT caused by climate change is a large-scale and long-term effect, which has been confirmed by many studies conducted around the world (O'Reilly et al., 2003; O'Reilly et al., 2015). However, some serious ecological environmental problems associated with lakes have been driven by short-term environmental conditions. Missaghi et al. (2017) found that the Minnetoka LSWT increased up to 4 ℃ during the ice-free seasons, resulting in a significant reduction in the size of the freshwater fish habitat. O'Reilly et al. (2003) showed that the Tanganyika LSWT had been increasing at a rate of 0.1 ℃/decade since 1913 with climate warming and regional wind speed reduction. This warming had also affected the stability of the lake, as a result of which, the primary productivity may have decreased by about 20%, implying a roughly 30% decrease in fish yields. At the same time, lake warming would lead to an increase in the frequency of cyanobacteria bloom outbreaks by 20% (O'Reilly et al., 2015). Sharma et al. (2015) constructed a dataset of climate drivers (near surface air temperature, surface solar radiation, cloud cover) and lake morphology parameters (longitude, latitude, altitude, lake area, etc.) that affected LSWT changes in 291 lakes worldwide (Sharma et al., 2015). Based on this dataset, O’Reilly et al. (2015) demonstrated that the regional near-surface air temperature and geomorphology had a greater impact on LSWT than other factors. Schmid & Koster (2016) showed that increases in near-surface air temperature and surface solar radiation were the main reasons for the increase in LSWT in spring and summer, with contribution rates of 60% and 40%, respectively. In addition to near-surface air temperature and surface solar radiation, several other factors have also been shown to affect the LSWT (Schmid & Koster., 2016). Increased wind speed tended to decrease the LSWT due to increased evaporation (Tanentzap et al., 2008; Valerio et al., 2015; Woolway et al., 2018). Secchi depth can be used to calculate the light attenuation, and stronger light attenuation was found to cause the LSWT to rise in spring and summer, but the shallower thermocline caused the LSWT to fall faster in autumn (Heiskanen et al., 2015; Hocking &

Straskraba., 1999; Rinke et al., 2010). In particular, LSWT values in daytime or nighttime showed different warming characteristics, and need to be considered separately, especially in small and shallow lakes (Wan et al., 2017; Woolway et al., 2016).

To sum up, the observation that LSWTs are gradually rising has become a consensus in the academic community. Climate warming was the main factor leading to increasing LSWTs, but the impact of differences in spatial heterogeneity on LSWT is also worthy of in-depth study. Therefore, based on previous research (Yang et al., 2016, 2017, 2018, 2019), the 11 naturally formed lakes in the Yunnan Guizhou Plateau were selected for study, the LSWT change characteristics from January 2001 to December 2018 were analyzed, the contribution rates of six factors (near surface air temperature, surface solar radiation, etc.) were quantified, and the characteristics and the relationships of those six factors to different lake attributes and lake types are discussed. This work provides methodological reference and theoretical support for the analysis of the spatial heterogeneity of regional LSWT increases.

2 Data and methods

2.1 Study area

The Yunnan-Guizhou Plateau is one of the most typical karst landforms in the world. The 11 naturally formed plateau lakes support abundant natural resources, diverse ethnic cultures, and unique ecological environments in the Yunnan-Guizhou Plateau. The differences in lake depth, eutrophication, water quality, and land use types in the watershed can provide abundant research samples. These lakes reserve nearly 5% of the freshwater resources of China. They all have a surface area of more than 25 km^2, including nine lakes in Yunnan Province (Dianchi, Erhai, Fuxian, Chenghai, Lugu, Yilong, Qilu, Xingyun, and Yangzonghai Lake), 1 in Guizhou Province (Caohai Lake), and 1 in Sichuan Province (Qionghai Lake). The names and major characteristics of these lakes are shown in Table A1 and Table A2, respectively, and their geographical locations are shown in Fig. 1. Among these lakes, Fuxian and Lugu Lakes are the second and third deepest freshwater lakes in China, while Dianchi and Erhai Lakes are the first and second largest freshwater lakes in Yunnan Province, respectively. Chenghai Lake is the second largest freshwater lake in western Yunnan Province, and Qionghai Lake is the second largest freshwater lake in Sichuan Province. Dianchi, Erhai and Fuxian Lakes each has a surface area of more than 200 km^2, while the other lakes have an area of less than 80 km^2 each. From 2005 to 2018, the eutrophication status of Dianchi Lake was hyper eutropher, Fuxian and Lugu Lakes were oligotropher, 3 lakes (Yilong, Qilu and Xingyun Lake) were middle eutropher, and the other 5 lakes were mesotropher. The annual mean of LSWT-day of 4 lakes (Chenghai, Lugu, Yilong, and Qionghai Lakes) was higher than 20 °C, while that of LSWT-night of 2 lakes (Lugu and Caohai Lakes) was lower than 10 °C (Table A2).

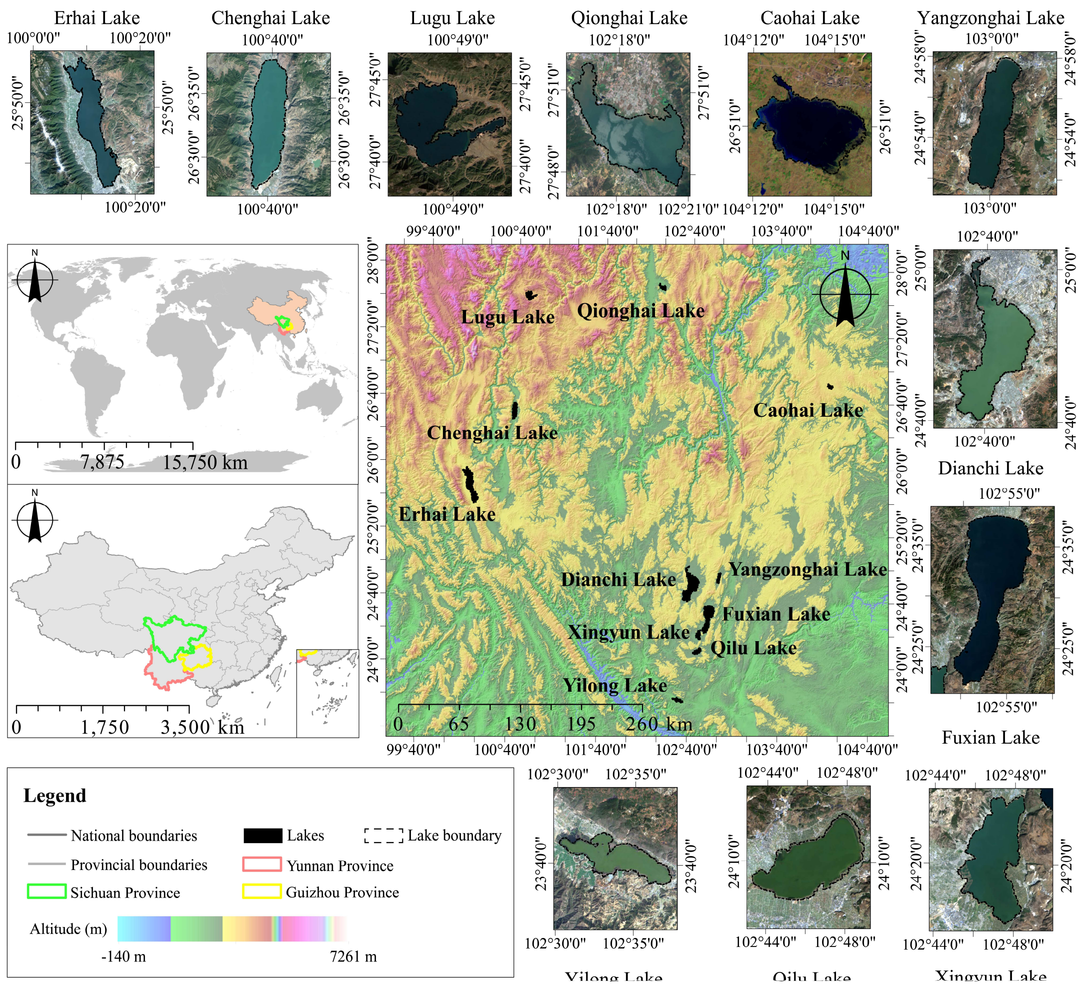


Fig. 1 The location of study area.

2.2 Data sources

This study collected data, including lake surface water temperature (LSWT), near surface air temperature (NSAT), surface pressure (SP), surface solar radiation (SSR), total cloud cover (TCC), wind speed (WS), and Secchi depth (SD) from January 1, 2001 to December 31, 2018. Specific descriptions of the data are presented in Table A3.

For this data set, LSWT values were extracted from MOD11A2 remote-sensing images, which were 8-day and 1-km resolution MODIS/Terra LST level 3 synthetic products, obtained by the NASA Earth Observation System Data and Information System (EOSDIS). The Modis Reprojection Tool (MRT) resampled the data into the GeoTiff format, re-projected, created mosaics, and replaced the cloud-affected cell values with Null (Wan et al., 2017). The time distribution of missing values for remote sensing images is shown in Fig. A1. Missing pixels were filled by linear interpolation, and the average bias was found to be 1.21 □ (RMSE = 2.21, R^2 = 0.82). Secchi depth was derived from MOD09GA remote sensing images, which were daily and 500-m-resolution synthetic products with MODIS/Terra's surface reflectance level-3. A long short-term memory (LSTM) network was used to derive these values with a high accuracy (Bias = 0.21 m, RMSE = 0.14, MAE = 0.11), and the method used for this is described detail in Appendix B. The data for near-surface air temperature (Bias = 1.21 □), surface pressure (Bias = 131.16 Pa), surface solar radiation (Bias = 48.28 W/m^2), total cloud cover (Bias = 9.32%), and wind speed (Bias = 1.91 m/s) were obtained from the ERA-Interim dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF), and wind speed values were calculated from the *u* and *v* wind speed components (10-meter u/v-wind component), as shown in Eq. (1). Specifically, WS_i is the wind speed on the i^{th} day, while *u* and *v* are the 10-meter u/v-wind components, respectively.

$$WS_i = \sqrt{u_i^2 + v_i^2} \tag{1}$$

2.3 Methods

2.3.1 Trend analysis method

Theil-Sen slope (TS_{Slope}) estimation is a nonparametric estimation method that was used here to estimate the change rate (CR) of time-series data. This estimation method can handle censored regression models and is insensitive to outliers. For skew and heteroscedastic data, it is more accurate than non-robust simple linear regression, even for normally distributed data, and non-robust least squares. This method has obvious advantages, especially for data with chaotic properties. The expression for the Theil-Sen slope is given in Eq. (2), where *median* is the median function, x_i and x_j are series data, t_i and t_j are the time points corresponding to the series data, n is the series length, and i and j are the series number ($1 \leq i < j \leq n$). When $TS_{Slope} > 0$, this indicates an upward trend; otherwise, it indicates a downward trend. The higher the value of $|TS_{Slope}|$, the stronger the trend.

$$TS_{Slope}=median\left(\frac{x_j-x_i}{t_j-t_i}\right) \tag{2}$$

In order to express the change rates of parameters in different scales, this paper uses a comprehensive change rate (CCR), which avoids the limitations of a single dimension. The comprehensive change rate was calculated as the average of the annual change rate (TS_{year}), the seasonal (spring, summer, autumn and winter) change rate (TS_{season}), and the monthly (January to December) change rate (TS_{month}), as shown in Eq. (3), where *mean* represents the mean function and the mean comprehensive change rate (MCCR) is the average CCR of 11 lakes. For the mean comprehensive warming rate (MCWR), only the warming rates are considered and the cooling rates are excluded.

$$TS_{Comprehensive}=mean(TS_{year}+TS_{season}+TS_{month}) \tag{3}$$

2.3.2 Contribution analysis method

The ΔR^2 values of multivariate regressions were used to calculate the contribution rates. A detailed description of this analysis method is presented in Appendix B (2.4 Multivariate regression analysis). ΔR^2 can be used to describe the explanatory power of a newly added independent variable to the dependent variable, as shown in Eq. (4). Here, R^2_{before} is the R^2 of the original regression model and R^2_{after} is the R^2 of the regression model after adding the new independent variable.

$$\Delta R^2 = R^2_{after} - R^2_{before} \quad (4)$$

2.3.3 Correlation analysis method

Pearson's correlation coefficient is one of the metrics used to describe the relationships among the variables. This comparison method uses the covariance matrix of the data to evaluate the strength of the relationship between two vectors. Normally, the Pearson's correlation coefficient between two variables α_i and α_j can be calculated as shown in Eq. (5), where $cov(\alpha_i,\alpha_j)$ is the covariance, $var(\alpha_i)$ is the variance of α_i, and $var(\alpha_j)$ is the variance of α_j. Pearson's correlation coefficient was also used in cross-correlation analysis (Podobnik et al., 2008).

$$R(\alpha_i,\alpha_j) = \frac{cov(\alpha_i,\alpha_j)}{\sqrt{var(\alpha_i) \times var(\alpha_j)}} \quad (5)$$

3 Results

3.1 Characteristics of Lake Surface Water Temperature

The LSWT of the 11 lakes showed an overall upward trend, and the warming rate of LSWT-day was higher than that of LSWT-night (as shown in Fig. 2 and Fig. A2). In LSWT-day, Lugu and Yangzonghai Lakes showed a downward trend, while in LSWT-night, Qilu, Xingyun, and Yilong Lakes showed a downward trend, among which Qilu and Yilong Lakes exhibited particularly sharp declines (as shown in Table A4).

(1) Monthly Analysis

From 2001 to 2018, the monthly mean LSWT-day values of Yangzonghai and Lugu Lakes showed a downward trend (CR_{YZHL}=-0.14 □/decade, CR_{LGL}=-0.27 □/decade) with a mean cooling rate of -0.2 °C/decade. The remaining nine lakes showed an upward trend with a mean warming rate of 0.41 °C/decade and a mean change rate of 0.3 °C/decade. The monthly mean LSWT-night in four lakes (Dianchi, Xingyun, Qilu, and Yilong Lakes) showed a downward trend (CR_{DCL}=-0.01 □/decade, CR_{XYL}=-0.12 □/decade, CR_{QLL}=-0.46 □/decade, CR_{YLL}=-0.98 □/decade) with a mean cooling rate of -0.39 □/decade. The other 7 lakes showed an upward trend with a mean warming rate of 0.17 □/decade and a mean change rate of -0.03 □/decade. In LSWT-day, all lakes showed a downward trend from December to April and an upward trend in the other months (from May to November). In LSWT-night, 11 lakes showed an upward trend in May and September to October, and a downward trend in the other months of the year (January to April, June to August, and November to December).

(2) Seasonal analysis

From 2001 to 2018, the mean LSWT-day in 2 lakes (Yangzonghai and Lugu Lakes) decreased (CR_{YZHL}=-0.03 □/decade, CR_{LGL}=-0.25 □/decade) and the mean cooling rate was -0.14 □/decade. The mean warming rate in the other lakes (9 lakes) was 0.44 □/decade and the mean change rate was 0.34 □/decade. The mean LSWT-night in 3 lakes (Xingyun, Qilu, and Yilong Lakes) decreased (CR_{XYL}=-0.06 □/decade, CR_{QLL}=-0.26 □/decade, CR_{YLL}=-0.89 □/decade) with a mean cooling rate of -0.4 □/decade, while the other lakes (8 lakes) showed an upward trend with a mean warming rate of 0.28 □/decade and a mean change rate of 0.09 □/decade.

In the spring, the mean LSWT-day of four lakes (Yangzonghai, Lugu, Qionghai, and Caohai Lakes) showed a downward trend (CR_{YZL}=-0.84 □/decade, CR_{LGL}=-1.27 □/decade, CR_{QHL}=-0.1 □/decade, CR_{CAHL}=-0.65 □/decade), while the other 7 lakes showed an upward trend with a mean warming rate of 0.64 □/decade, mean cooling rate of -0.71 □/decade, and mean change rate of 0.15 □/decade. The mean seasonal LSWT-day of 2 lakes (Erhai and Lugu Lakes) showed a downward trend (CR_{EHL}=-0.53 □/decade, CR_{LGL}=-0.62 □/decade), while the other 9 lakes showed an upward trend with a mean warming rate of 0.9 □/decade. The mean cooling rate was -0.58 □/decade, and the mean rate of change was 0.63 □/decade. In autumn, these lakes all showed an upward trend in LSWT-day, with a mean warming rate of 0.7 □/decade; in winter, the LSWT-day of four lakes (Fuxian, Qilu, Yilong, and Caohai Lakes) showed an upward trend (CR_{FXL}=0.08 □/decade, CR_{QLL}=0.28 □/decade, CR_{YLL}=0.06 □/decade, CR_{CAHL}=0.34 □/decade). The other 7 lakes showed a downward trend, with a mean warming rate of 0.19 □/decade, a mean cooling rate of -0.3 □/decade, and a mean change rate of -0.12 □/decade.

The mean LSWT-night in spring of 2 lakes (Qilu and Yilong Lakes) showed a downward trend (CR_{QLL}=-0.51 □/decade, CR_{YLL}=-0.62 □/decade), while the other lakes (9 lakes) showed an upward trend, with a mean warming rate of 0.17 □/decade, a mean cooling rate of -0.39 □/decade, and a mean change rate of 0.35 □/decade. The mean LSWT-night in summer of 4 lakes (Yangzonghai, Erhai, Lugu, and Caohai Lakes) showed an upward trend (CR_{YZHL}=0.07 □/decade, CR_{EHL}=0.05 □/decade, CR_{LGL}=0.2 □/decade, CR_{CAHL}=0.37 □/decade), while the other 7 lakes showed a downward trend, with a mean warming rate of 0.17 □/decade, a mean cooling rate of -0.52 □/decade, and a mean change rate of -0.27 □/decade. The seasonal mean LSWT-night of 2 lakes (Yilong and Qionghai Lakes) showed a downward trend in autumn (CR_{YLL}=-0.49 □/decade, CR_{QHL}=-0.19 □/decade), while the other nine lakes showed an upward trend, with a mean warming rate of 0.5 □/decade. The mean cooling rate was -0.34 □/decade and the mean change rate was 0.35 □/decade. The seasonal mean LSWT-night of five lakes (Dianchi, Xingyun, Qilu, Yilong, and Qionghai Lakes) in winter showed a downward trend (CR_{DCL}=-0.02 □/decade, CR_{XYL}=-0.09 □/decade, CR_{QLL}=-0.58 □/decade, CR_{YLL}=-1.05 □/decade, CR_{QHL}=-0.08 □/decade), while the other six lakes showed an upward trend. The mean warming rate was 0.19 □/decade, the mean cooling rate was -0.36 □/decade, and the mean change rate was -0.06 □/decade.

(3) Annual analysis

The annual mean LSWT-day in Lugu Lake showed a downward trend (CR_{LGL}=-0.02 □/decade). The mean warming rate of the other lakes was 0.46 □/decade, and the mean change rate was 0.41 □/decade. The annual mean

LSWT-night in 2 lakes (Qilu and Yilong Lakes) showed a downward trend (CR_{QLL}=-0.27 □/decade, CR_{YLL}=-0.61 □/decade) with a mean cooling rate of -0.44 □/decade. The other lakes showed an upward trend, with a mean warming rate of 0.24 □/decade and a mean change rate of 0.12 □/decade.

(4) Comprehensive change rate analysis

The comprehensive change rate of LSWT-day in 2 lakes (Yangzonghai and Lugu Lakes) showed a downward trend (CR_{YZHL}=-0.1 □/decade, CR_{LGL}=-0.25 □/decade) with a mean cooling rate of -0.17 □/decade. The other lakes showed an upward trend with a mean warming rate of 0.42 □/decade. The mean change rate was 0.31 □/decade. The comprehensive change rate of LSWT-night in 3 lakes (Xingyun, Qilu, and Yilong Lakes) showed a downward trend (CR_{XYL}=-0.1 □/decade, CR_{QLL}=-0.4 □/decade, CR_{YLL}=-0.94 □/decade) with a mean cooling rate of -0.48 □/decade, while the other lakes showed an upward trend with a mean warming rate of 0.19 □/decade. The mean change rate was 0.01 □/decade.

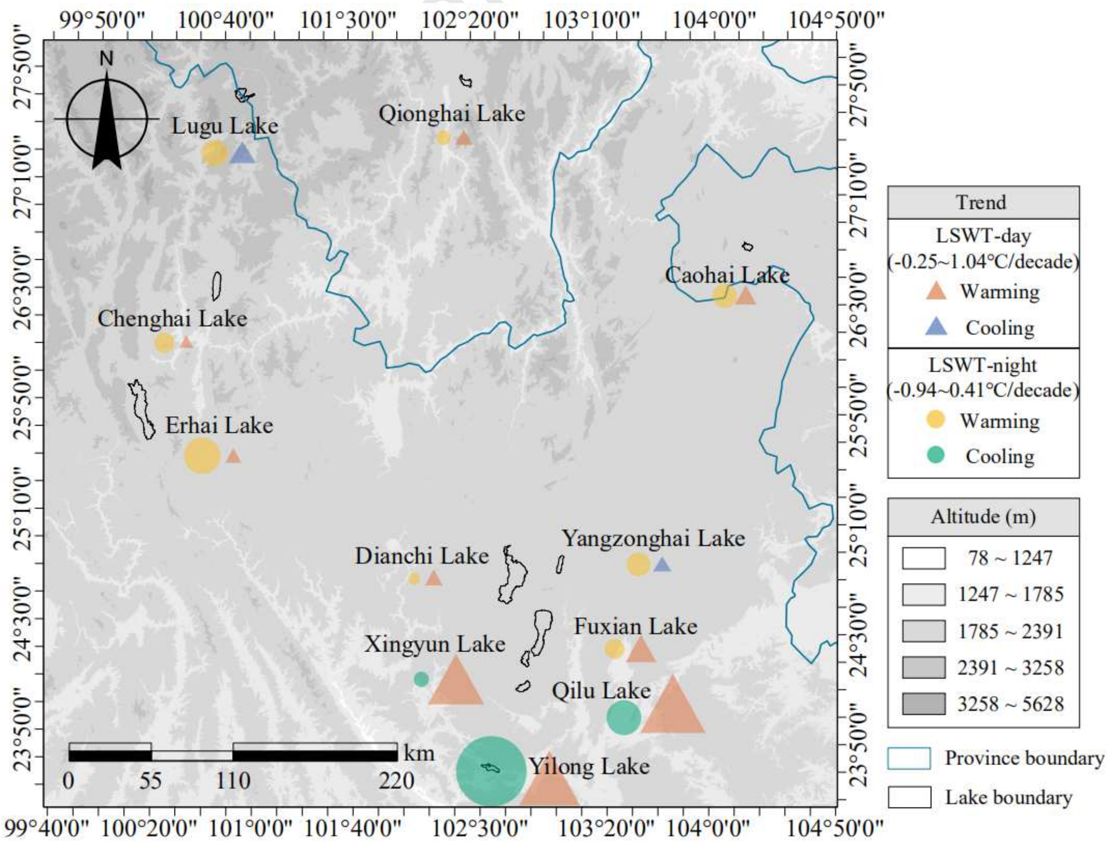


Fig. 2 LSWT-day/night trend for 11 lakes. The comprehensive change rate was represented by marks (circles and triangles) size, and the trend was represented by different colors.

3.2 Correlation and contribution rate

3.2.1 Correlation analysis

The Pearson's correlation coefficient analysis results for six factors for each lake and the monthly mean LSWT-day/night are shown in Fig. 3. For the 11 lakes, the correlation between NSAT and LSWT was the highest ($R_{NSAT\text{-}day}$=0.83, $R_{NSAT\text{-}night}$=0.81), followed by that between SSR and TCC ($R_{SSR\text{-}day}$=0.46, $R_{TCC\text{-}day}$=0.54, $R_{SSR\text{-}night}$=0.66, $R_{TCC\text{-}night}$=0.38). SD was the lowest ($R_{SD\text{-}day}$=-0.017, $R_{SD\text{-}night}$=0.026), while SP and WS were negatively correlated ($R_{SP\text{-}day}$=-0.46, $R_{WS\text{-}day}$=-0.19, $R_{SP\text{-}night}$=-0.32, $R_{WS\text{-}night}$=-0.19).

According to the analysis for each lake, the factors with Pearson's correlation coefficients higher than 0.6 were considered as high correlation factors (as shown in Table A5). For LSWT-day, the most highly correlated factors of Yilong and Caohai Lakes were found to be SP, SSR, and NSAT; for Xingyun and Yangzonghai Lakes, SP and NSAT; for Qilu Lake, NSAT; for Lugu Lake, SSR; and for the other five lakes (Dianchi, Fuxian, Erhai, Chenghai, and Qionghai Lakes) the high correlation factors were found to be NSAT and TCC. For LSWT-night, the high correlation factors of Yilong Lake were SP, SSR and NSAT, those of Fuxian and Chenghai Lakes were NSAT, those of Erhai Lake were NSAT and TCC, and those of the other 7 lakes (Dianchi, Xingyun, Qilu, Yangzonghai, Lugu, Qionghai, and Caohai Lakes) were SSR and NSAT.

Of the correlations between different factors and LSWT-day (as shown in Fig. A3(a) ~ (f)), those of SP and TCC were lower, but relatively higher in summer; those of SSR and NSAT were higher, especially in winter, but lower in summer and autumn; those of SDs in all four seasons were close, slightly higher in winter, and relatively lower in spring and summer; that of WS was lower in summer, but higher in other seasons.

In terms of the correlations between different factors and LSWT-night (as shown in Fig. A3(g) ~ (l)), the four seasons resulted in clear changes, except for SD and WS. The correlation with SD in spring was lower, but higher in autumn and winter. The correlation with WS was higher in spring, but the correlation values in other seasons were close. In autumn, SP showed an opposite correlation compared to the other seasons, that is, higher in autumn and lower in other seasons. The correlation coefficients of SSR were closer in autumn and winter, as were those in spring and summer. The correlation with NSAT was higher in winter, lower in summer, and close in spring and autumn. The correlation coefficients of TCC were close in summer and winter, but higher in autumn.

Cross-correlation analysis results are shown in Table A6, and all factors were found to be statistically significant (α<0.05) except SD. In general, TCC exhibited a first-order lag, SSR and SP for LSWT-day exhibited first-order lead, SSR exhibited 5th-order lag for LSWT-night, and WD exhibited 2nd-order lag (for LSWT-day) and 8th-order lag (for LSWT-night). The different factors almost maintained the same time-lag at different scales. It is necessary to mention that SP exhibited a different time-lag in each lake type. In terms of LSWT-day, the natural lakes (Yang et al., 2019) were different from the other types. Urban and semi-urban lakes (Yang et al., 2019) exhibited 5th-order lag, while natural lakes exhibited 1st-order lead. For LSWT-night, semi-urban and natural lakes were close, with 5th/4th-order lag respectively, while urban lakes showed 2nd-order lead. The trend in the cross-correlation coefficients was almost same as that in the Pearson's coefficients, but the values were higher.

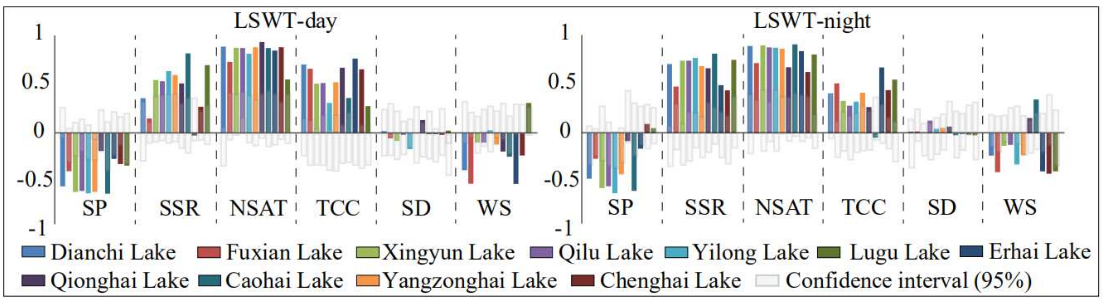


Fig. 3 The Pearson's correlation coefficient analysis results for six factors of each lake with monthly mean LSWT-day/night.

3.2.2 Contribution rate analysis

The overall contribution rates of each factor to LSWT-day/night are shown in Fig. 4. The multiple linear regression equations are shown in Table A7 (Eq. (A1) ~ (A2)).

In these equations, $LSWT_{day}$ and $LSWT_{night}$ represent LSWT-day and LSWT-night, respectively. Two equations can express the contributions of six variables to LSWT-day/night, which were 61.94% and 64.40%, respectively; the remaining 38.06% and 35.60% contributions are attributed to other factors. For LSWT-day, NSAT, SSR, and TCC contributed 42.79%; for LSWT-night, NSAT and SSR contributed 44.34%; for LSWT-day and LSWT-night, NSAT contributed the most ($ConR_{day}$ =18.50 %, $ConR_{night}$ = 30.41%), followed by SSR ($ConR_{day}$ =11.74 %, $ConR_{night}$ =13.93 %), while WS contributed the least ($ConR_{day}$ =6.11 %, $ConR_{night}$ = 0.00%).

The mean contribution rates of the six factors to LSWT-day/night were found to be 81.02% and 75.96%, respectively, and that of NSAT was the highest ($ConR_{day}$ = 34.85%, $ConR_{night}$ = 32.77%); SSR and TCC exhibited the second highest rates ($ConR_{SSR\text{-}day}$=13.62%, $ConR_{SSR\text{-}night}$=21.88%, $ConR_{TCC\text{-}day}$=16.05%, $ConR_{TCC\text{-}night}$=8.84%); that of SD was the lowest ($ConR_{day}$ = 0.19%, $ConR_{night}$ = 0.17%). For LSWT-day, NSAT, TCC, SSR and SP were the main impact factors ($ConR_{day}$ = 76.16%). For LSWT-night, NSAT and SSR were the main impact factors ($ConR_{day}$ = 54.65%). For all 11 lakes, the contribution rates of each factor to LSWT-day/night were different, as shown in Table A8. The variables with contribution rates higher than 10% were regarded as the main impact factors.

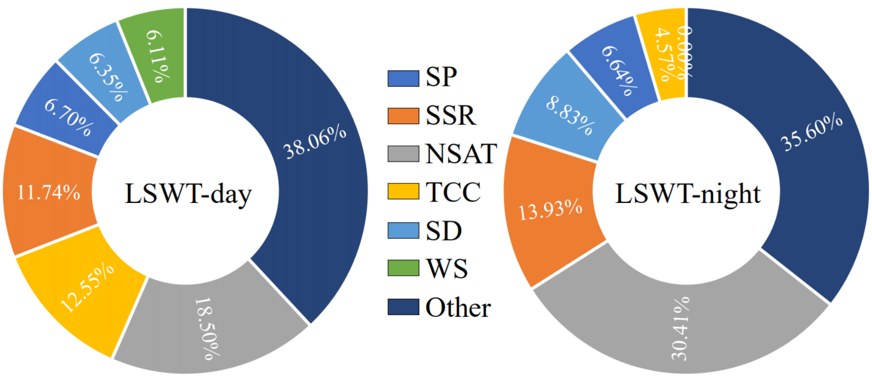


Fig. 4 The overall contribution rate of six factors to LSWT-day/night for 11 lakes.

4 Discussion

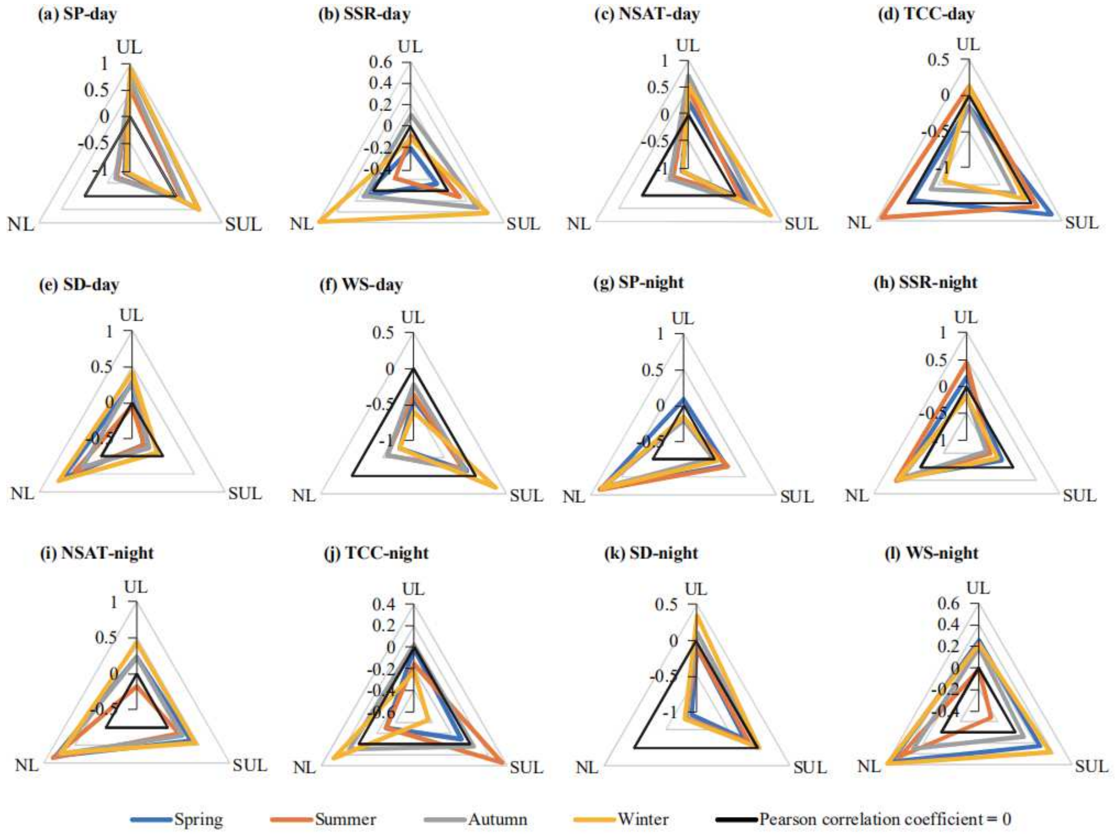
From 2001 to 2018, the LSWT-day/night values of most lakes showed a warming trend. The mean comprehensive change rate of LSWT-day was 0.31 □/decade, which is approaching global lake warming rates (O'Reilly., 2015). The mean comprehensive change rate of LSWT-night was 0.01 □/decade, the mean comprehensive change rate of NSAT was 0.25 □/decade, and the mean comprehensive change rates of NSAT and LSWT-day were relatively close. The rising trend of LSWT-day in the 11 naturally formed lakes was consistent with that observed in most lakes in the world (O'Reilly et al., 2015). The governance plan for urbanization expansion put forward by the government had a certain impact on LSWT changes in the watershed. The average altitude of the Yunnan-Guizhou Plateau is about 1881 m, and the solar radiation in the east is lower than that in the west. The distribution of solar radiation is relatively uniform in each month of the year. The population distribution is relatively concentrated in the low-altitude areas of central and southeast Yunnan. With serious urbanization and expansion, the number of impervious surfaces increased, resulting in increased runoff temperature. The influence of human activities had caused changes in the regional land surface temperature, humidity, air convection, and other factors related to urban surface area, resulting in urban heat island and rain island effects (Lawrence., 1971; Jáuregui & Romales., 1996; Adamowski & Prokoph., 2013), which in turn affected the LSWT. Furthermore, in the past thirty years, the total area of lakes in the Yunnan-Guizhou Plateau showed a trend of rising first and then falling, which was mainly attributed to the four-year lingering drought and man-made damage to the lake environment from 2009 to 2012 (Xiao et al., 2018). The main reason for the decrease in lake area was urban expansion, and lake shrinkage would also cause the LSWT rise. The spatial heterogeneity of the LSWT changes was related to lake morphology parameters (Woolway & Merchant, 2017, 2018) and human activities (Yang et al., 2019).

4.1 Lake surface water temperature variation characteristics of Different lake types

In previous studies (Yang et al., 2019), the 11 lakes considered here were divided into three types: urban lakes (Dianchi and Qilu Lakes), semi-urban lakes (Erhai, Yilong, Qionghai, Yangzonghai, and Caohai Lakes) and natural lakes (Fuxian, Xingyun, Lugu, and Chenghai Lakes). On this basis, LSWT-day/night change trends in different lake types were analyzed (as shown in Fig. 5). For LSWT-day, all the three lake types exhibited rising values, the comprehensive warming rate of urban lakes was higher than that of the others, and the warming rates of semi-urban and natural lakes were almost the same (CR_{UL}=0.58 □/decade, CR_{SUL}=0.25 □/decade, CR_{NL}=0.26 □/decade). For LSWT-night, urban and semi-urban lakes showed a cooling trend, while natural lakes showed a warming trend (CR_{UL}=-0.19 □/decade, CR_{SUL}=-0.0039 □/decade, CR_{NL}=0.12 □/decade), and the cooling rates of Qilu and Yilong Lakes were higher (CR_{QLL}=-0.4 □/decade, CR_{YLL}=-0.94 □/decade). Apart from these lakes (Qilu and Yilong Lakes), urban and semi-urban lakes showed warming trends (CR_{UL}=0.03 □/decade, CR_{SUL}=0.23 □/decade).

Considering the correlations between each factor and LSWT-day, the seasonal differences in SP and NSAT were small, while the values for urban and semi-urban lakes were higher than those of natural lakes. The SD of natural lakes was higher than that of the other lakes, and the WS of semi-urban lakes was higher, especially in the winter. SSR and TCC changed greatly with the season. The SSR was higher in spring and winter for natural lakes, while summer and autumn showed higher values for urban and semi-urban lakes. For TCC, semi-urban lakes were higher in spring, natural lakes were higher in summer, urban and semi-urban lakes were higher in winter, and TCC showed little variation in autumn. SP and NSAT were closely related to the urban heat island effect (Adamowski & Prokoph., 2013) and were greatly affected by human activities, so natural lakes showed lower values than the other lakes. The SD of the natural lakes was higher, and the fluctuation range was larger than that of the other lakes, so the correlation coefficients of SD for urban and semi-urban lakes were lower. Most of the semi-urban lakes were located in the southern part of the Yunnan-Guizhou Plateau, which is the low-altitude region. WS was affected by terrain and climate, and values were smaller (Fan & Thomas., 2013). With dense cities, WS and LSWT were more affected by human activities, so the correlation was higher than for the other areas. TCC was closely related to the rain island effect (Lawrence., 1971; Jáuregui & Romales., 1996). In winter, urban heat emissions were higher than in other areas, so the natural lakes exhibited lower values.

In LSWT-night, there were little seasonal differences for SP and SD. SP was higher in natural lakes, SD was higher in urban and semi-urban lakes, and SSR was higher in natural and urban lakes. NSAT was higher in the natural lakes, WS in summer was higher in natural and urban lakes, and changed little in the other lakes, while WS was relatively higher in the natural lakes. TCC changed more. In spring and summer, urban and semi-urban lakes exhibited higher TCC, autumn was gentle, and in winter TCC was higher for natural lakes. The intensity of human activity is greatly reduced at night, but still remains much higher in the urban areas than in other areas (Cao et al., 2009), especially in summer and autumn; therefore, urban and semi-urban lakes were more affected by human activities. NSAT was more sensitive to human activities than LSWT (Ye et al., 2013). The correlation between LSWT-night and NSAT (urban and semi-urban lakes) was lower than for natural lakes, and the influence of human activities at night cannot be ruled out. NSAT in non-urban areas at night was affected by fewer other factors, so the correlation coefficient for natural lakes was higher.



Note: UL = Urban lake; SUL = Semi-urban lake; NL = Natural lake

Fig. 5 The Pearson's correlation coefficient analysis results for six factors of each lake type with seasonal mean LSWT-day/night.

In terms of the contribution of each factor to the LSWT of different lake types, the regression equations are shown in Table A7 (Eq. (A3) ~ (A8)), and the contribution rates are shown in Table A9. The overall contribution of the six factors for the three lake types was higher than 60%, while the urban lakes exhibited the highest values ($ConR_{all\text{-}day}$=83.60%, $ConR_{all\text{-}night}$=78.49%). For urban and semi-urban lakes, the main factors affecting LSWT-day were found to be SSR, NSAT, and TCC, of which NSAT was the most important impact factor ($ConR_{UL}$=43.49%, $ConR_{SUL}$=38.12%). SSR and NSAT were found to be the main factors affecting LSWT-night, with contributions reaching 65.95% and 56.52%, respectively. For natural lakes, the impact of the six factors on LSWT-day was small. The main contributing factors were SP, SSR, TCC, and SD. The contribution rate of the main factors was 52.18%. SP, NSAT, and SD were determined to be the main factors affecting LSWT-day, with a contribution rate of 64.56%. Schmid & Koster (2016) showed evidence that SSR and NSAT were the main influencing factors of LSWT, and that the contribution rate of SSR was ~60%, while that of NSAT was ~40%. These results are slightly different from ours. The above results show that the driving factors and their contributions are not the same for different types of lakes, which might be related to the intensity of human activity and the distribution of differences in lake morphology.

4.2 Lake surface water temperature variation characteristics with different morphological

Becker & Daw (2005) and Woolway & Merchant (2017, 2018) showed that the morphological characteristics of lakes had a significant impact on LSWT, and the main influencing factors included lake area, depth, and storage. In this paper, the 11 lakes were divided into three types by K-Means clustering with these factors, as shown in Table A10. The areas of Fuxian, Dianchi, and Erhai Lakes are all greater than 200 km^2, while the areas of the other lakes were within 25~80 $km^{2.}$ The storage and depth of Fuxian Lake are the highest of the 11 lakes. Dianchi and Erhai Lakes are close to the urban area. In LSWT-day, Dianchi, Erhai, and Fuxian Lakes were mainly affected by NSAT, TCC, and WS, while NSAT and TCC had particularly high contribution rates ($ConR_{NSAT2}$=28.57%, $ConR_{NSAT3}$=37.20%, $ConR_{TCC2}$=23.30%, $ConR_{TCC3}$=26.91%), while other lakes were mainly affected by SP, SSR, NSAT, and TCC, of which NSAT had the highest contribution rate ($ConR_{NSAT1}$=35.06%). In LSWT-night, Dianchi, Erhai, and Fuxian Lake were mainly affected by SSR and NSAT. Under the impact of TCC, NSAT had a high contribution rate ($ConR_{NSAT2}$=27.05%, $ConR_{NSAT3}$=38.13%), while other lakes were mainly affected by SSR and NSAT, with a contribution rate of 56.02%. Even if the attributes of the lakes were different, NSAT was still the most important factor affecting LSWT, and SSR was the second main factor. In the small, shallow, and low-storage lakes, LSWT-day was more affected by SP and SSR. For large lakes (Fuxian, Dianchi, and Erhai Lakes), WS had a greater impact on LSWT-day/night.

In summary, considering the dual impact of human activities and climate change, urban and semi-urban lakes more strongly influenced by human activities were more affected by SSR and NSAT. And the contributions of the six factors were higher in these two lake types, indicating that the urban heat island effect caused by the expansion of impervious surface area and the increase in surface runoff temperature in the areas with more human activities resulted in higher LSWT warming rates. For LSWT-day, TCC was also a factor with great influence. More cloud-enhanced atmospheric counter radiation and atmospheric insulation enabled NSAT to stay in a higher state. For natural lakes, SP and SD were both important factors for LSWT. SD can directly reflect the water quality of a lake and indirectly reflect the changes in lake water quality caused by human activities. The impact of NSAT on LSWT-day was smaller, which indicates that lakes were more sensitive to natural factors in the case of less point source pollution and a lake less affected by human activities. Moreover, the higher contribution rate of SD also reflected the fact that lakes were more affected by humans.

5 Conclusion

Based on the dataset of LSWT-day/night, SP, SSR, NSAT, TCC, WS, and SD, this paper analyzed the LSWT-day/night values of the 11 major naturally formed lakes in the Yunnan-Guizhou Plateau from January 1, 2001 to December 31, 2018, explored the main driving factors affecting the change of LSWT-day/night, and quantified the impact degree of each factor. The characteristics of and relationships between the factors affecting LSWT in lakes of different types and attributes were revealed, which will provide new insight for further research into lake environments.

(1) In the past 18 years, the LSWT-day/night values of all 11 lakes showed a warming trend, and LSWT-day was higher than LSWT-night. In terms of LSWT-day, nine lakes exhibited rising temperatures with a mean comprehensive warming rate of 0.42 □/decade, while Yangzonghai and Lugu Lakes showed downward trends. In LSWT-night, 8 lakes showed upward trends, with a mean comprehensive warming rate of 0.19 □/decade, while Xingyun, Qilu, and Yilong Lakes showed decreasing trends.

(2) The results of correlation analysis showed that NSAT and LSWT day/night had the strongest correlation for all the 11 lakes ($R_{NSAT\text{-}day}$=0.83, $R_{NSAT\text{-}night}$=0.81), while the correlations between TCC and LSWT-day and SSR and LSWT-night were the second largest ($R_{TCC\text{-}day}$=0.54, $R_{SSR\text{-}night}$=0.66). Correlation analysis for each lake showed that NSAT and LSWT-day were the most strongly correlated, while SSR and SP were the second most strongly correlated pair. On the seasonal scale, the correlations between NSAT and LSWT-day were constant over each of the four seasons, while the correlations between NSAT and LSWT-night, SSR and LSWT-day/night varied greatly.

(3) Contribution rate analysis showed that NSAT and SSR were the most important factors affecting LSWT-day/night, and their contribution rates reached 30.24% and 44.34%, respectively. The LSWT-day values of smaller, shallower, and lower-storage lakes were more affected by SP and SSR. For larger lakes, the LSWT-day values were more affected by WS; the LSWT-night values were more affected by TCC. The influence of SSR and NSAT in urban and semi-urban lakes was more serious, which indicates that the urban heat island effect caused by the expansion of impervious surfaces and increases in runoff surface temperature in areas with higher degrees of human activity are responsible for higher LSWT warming rates. For natural lakes, the decrease in SD was important to the increase in LSWT, which indirectly suggests that the impact of human activities on the water quality of lakes has caused the LSWT to warm.

Acknowledgements

This study was financially supported by the National Natural Science Foundation of China [41761084], the China High Technology Research and Development Program 863 [2012AA121402], and the Yunnan Natural Science Foundation of China [2016FD020]. Kun Yang and Zhenyu Yu contributed equally to this work and should be considered co-first authors.

Appendix A. Supplementary chart

Supplementary chart related to this paper can be found at https://pan.baidu.com/s/1pTr4qN78V-rTnwmrWV5TQg (Extract code: g3u0).

Appendix B. Supplementary method description

Supplementary method description of Secchi depth inversion related to this paper can be found at https://pan.baidu.com/s/1Dmxx95UYU-Qeu6vmVp9asg (Extract code: 9sw2).

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Highlights:

- The heterogeneity of LSWT warming of 11 major plateau lakes were discussed
- 6 main factors impact on LSWT were analyzed quantitively
- LSWT changing heterogeneity was revealed from lake type and morphometry perspective

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: