RESEARCH ARTICLE

Spatiotemporal variation of potential evapotranspiration and its dominant factors during 1970–2020 across the Sichuan-Chongqing region, China

Qingzhou Zheng¹, Jun He¹*, Mengsheng Qin², Xia Wu³, Tiantian Liu¹, Xiaolin Huang⁴

¹ Chongqing Meteorology Bureau, Chongqing, China, ² Yangzhou Meteorology Bureau, Yangzhou, China, ³ Baotou Meteorology Bureau, Baotou, China, ⁴ Nanjing University of Information Science & Technology, Nanjing, China

* geyanghe@163.com

Abstract

Analyzing the primary factors of potential evapotranspiration (PET) dynamic is fundamental to accurately estimating crop yield, evaluating environmental impacts, and understanding water and carbon cycles. Previous studies have focused on regionally average regional PET and its dominant factors. Spatial distributions of PET trends and their main causes have not been fully investigated. The Mann–Kendall test was used to determine the significance of long-term trends in PET and five meteorological factors (net radiation, wind speed, air temperature, vapor pressure deficit, relative humidity) at 56 meteorological stations in the Sichuan-Chongqing region from 1970 to 2020. Furthermore, this present study combining and quantitatively illustrated sensitivities and contributions of the meteorological factors to change in annual and seasonal PET. There was a positive trend in PET for approximately 58%, 68%, 38%, 73% and 73% of all surveyed stations at annual, spring, summer, autumn and winter, respectively. Contribution analysis exhibited that the driving factors for the PET variation varied spatially and seasonally. For stations with an upward PET trend, vapor pressure deficit was a dominant factor at all time scales. For stations with a downward PET trend, annual changes in PET mainly resulted from decreased wind speed, as did changes in spring, autumn and winter; decreasing net radiation was the dominant factor in summer. The positive effect of the vapor pressure deficit offset the negative effects of wind speed and net radiation, leading to the increasing PET in this area as a whole. Sensitivity analysis showed that net radiation and relative humidity were the two most sensitive variables for PET, followed by vapor pressure deficit in this study area. Results from the two mathematical approaches were not perfect match, because the change magnitude of the meteorological factors is also responsible for the effects of meteorological factors on PET variation to some extent. However, conducting sensitivity and contribution analysis in this study can avoid the uncertainties from using a single method and provides detailed and well-understood information for interpreting the influence of global climate change on the water cycle and improving local water management.
1 Introduction

It is widely accepted that climate change and human activities profoundly affect local water energy transfer and water balance processes, such as evapotranspiration (ET) [1, 2]. Changes in these processes can have serious consequences, including increased risk of flooding, exacerbated urban heat island and dry island effects, and deterioration of water quality [3, 4]. ET, together with precipitation and runoff, is a fundamental component of the hydrological cycle [5–7]. ET is important in energy, water and carbon cycles and is a key climate parameter when analyzing regional-scale activity of hydroclimatic change and water cycle [8, 9].

Potential evapotranspiration (PET) is water lost to the atmosphere from well-watered crops under optimum soil water conditions [3, 10]. The meteorological variables are the only factors impacting PET so that PET can be calculated from weather data [10, 11]. The Penman-Monteith (P-M) equation is a standard model for estimating PET that is recommended by the United Nations Food and Agriculture Organization (FAO) [10]. The P-M equation includes climate variables such as air temperature ($T_a$), net radiation ($R_n$) and wind speed ($W_s$) and is appropriate for humid conditions [7, 12–14].

The effects of different source parameters on PET have been investigated over different periods and in different regions. Many studies indicated that the decreased $W_s$ was mainly responsible for the decline of PET [7, 14, 15]. Another widely accepted explanation for the PET reduction is the decrease in solar radiation caused by increasing cloud cover [13, 16]. Moreover, many researchers have identified drivers of increases in PET. Some researchers revealed that the relative humidity (RH) was the decisive factor of the increase in annual PET in many regions, such as Wei River basin [6] and Zhejiang province [17]. Meanwhile, some other researchers attributed the elevated PET to the increased vapor pressure deficit (VPD) [4, 11, 18, 19]. Climate change is highly heterogeneous owing to differences in the study period and study regions. Therefore, future studies are needed to evaluate regional-scale change in PET and its dominant factors explicitly.

This study was carried out in the Sichuan–Chongqing (SC-CQ) region, located in the east of the Qinghai–Tibet Plateau [20–22]. This region was characterized by diverse geological and climatic features, resulting in uneven distributions of climate elements and natural resources [23, 24]. The SC-CQ region contains two megacities (Chengdu and Chongqing), and has a total population of 115.7 million [22, 23]. The Chinese government launched the national strategy for the development of western regions in 2000. Therefore, the SC-CQ region became the core growth area of Southwest China and has experienced dramatic urban expansion and population growth in recent decades, which has directly affected local weather and hydrology [25]. In areas with rapid urbanization and industrialization, the hydrologic cycle is sensitive to human activities and is more prone to climate change than other areas [3, 5]. Recently, serious water-related issues have led to increasing problems in the eco-hydrological environment in this region [21]. Disastrous intense floods, extreme droughts and a series of severe environmental and ecological problems have affected this area in recent times, which attracts wide attention to disaster mitigation and prevention [20, 26, 27]. In this context, identification of trends in PET and its contributing factors will enhance our understanding of the effects of climate change on future water balance and thus enable the formulation of effective policies for water resource management in this region [4, 5, 15].

Spatial heterogeneity in PET and its causal mechanisms are to be expected in the study area due to the changeable climate and the complex topography. Previous literature has only focused on average regional PET and climatic elements of a long record. The spatial distributions of drivers of PET have not been adequately considered, which may cause deviation of regional PET from the real situation [15]. Understanding the spatial differences of PET is of great importance for identifying the mechanisms and processes by which environmental
dynamics and anthropogenic activities influence regional hydrology in the study area [3, 5, 15]. Thus, more attention should be paid to the PET research on spatial patterns of the stations instead of regional averaging.

The aims of this study were: (1) to identify temporal and spatial variation in PET across the SC-CQ region from 1970 to 2020; (2) to identify spatial and seasonal differences in the driving factors of PET; and (3) to quantify the contributions and sensitivity of dominant climate factors to PET changes. This study presents a detailed investigation of the heterogeneous spatial distribution of PET dynamics and the associated contributing meteorological factors using advanced statistical methods and geographic information systems (GIS).

2 Data and methods

2.1 Study area and data sources

The Sichuan-Chongqing region (26°03′–34°19′N, 97°21′–110°11′E; Fig 1) is large (568402 km²) and includes 22 cities, including the two megacities Chengdu and Chongqing, which are the principal cities in Southwest China [28]. The region has a complex and diverse climate, controlled by subtropical humid monsoon climate and alpine climate, lying in the semi-humid and humid zone [21, 27]. Annual rainfall varies spatially from 600 to 1700 mm. Multiyear average Tₐ is highly heterogeneous across this region, ranging from −1 to 20 °C. The topography of the region is dominated by high mountains, deep basins and river valleys; elevation ranges from 20 to 7148 m, low-lying in the east and high in the west, descending from the northwest to the southeast [27, 29].

Observed daily maximum air temperature (T_max, °C), minimum air temperature (T_min, °C), mean air temperature (T_mean, °C), relative humidity (RH, %), wind speed at 2 m height (U₂, m/s) and sunlight duration (SD, h) were used to estimate PET. Long term (1970–2020) daily meteorological data from 56 meteorological stations in the SC-CQ region were provided and quality controlled by the China Meteorological Administration (http://www.cma.gov.cn/). The digital elevation model (DEM) of the study area (Fig 1) was provided by the Computer Network Information Center (http://www.gscloud.cn/). Missing data when time gaps were less than five days or greater than five days were respectively filled using linear interpolation and the multiyear mean values of those days [30].
2.2 FAO Penman–Monteith model for PET calculation

Various approaches have been developed to quantify PET. The FAO-56 P-M equation [31, 32] was chosen to calculate PET in the current study, because it has gained wide acceptance and is applicable in humid conditions [3, 11–13, 33].

The FAO-56 P-M equation is [10]:

\[
\text{PET} = \frac{0.408 \Delta (R_n - G) + \frac{900}{\gamma + 273} U_2 (e_a - e_s)}{\Delta + \gamma (1 + 0.34 U_2)}
\]

where PET is the daily potential ET rate (mm/d), \(\Delta\) is the slope of the saturated vapor pressure curve (kPa/˚C), \(R_n\) is net radiation (MJ/m\(^2\)/d), \(G\) is soil heat flux density (MJ/m\(^2\)/d; zero on the daily scale), \(\gamma\) is the psychrometric constant (kPa/˚C), \(T\) is mean daily air temperature (˚C), \(U_2\) is mean daily wind speed at 2 m height (m/s), \(e_s\) is saturated vapor pressure (kPa), and \(e_a\) is actual vapor pressure deficit (VPD, kPa).

2.3 Trend test

The Mann–Kendall (MK) test [34, 35] is highly recommended by the World Meteorological Organization for testing the significance of a hydro-meteorological data trend. The method offers many advantages, including being less sensitive to outlier data [1, 5]. In this study, the nonparametric MK trend test was employed to detect temporal trends in PET and concerned climatic elements for each meteorological station. In order to assess the effects of climate factors on PET, linear regression was used to calculate the trend slope of the climate factors. The slope of the linear regression line represents the mean temporal change in the meteorological factor. If the slope is positive, the meteorological variable shows an upward trend; if the slope is negative, the meteorological variable shows a downward trend.

2.4 Contribution and sensitivity analysis of factors controlling PET

Stepwise regression was adopted to quantitatively analyze the contributions of each meteorological variable to variation in PET for each meteorological station in the SC-CQ region during 1970–2020. The meteorological variables were the predictors, and PET was the dependent variable. The stepwise regression can be expressed as:

\[
\text{PET} = a_1 x_1 + a_2 x_2 + a_3 x_3 + \cdots + a_n x_n + b
\]

where \(x_1, \ldots, x_n\) are the values of the meteorological variables, \(a_1, \ldots, a_n\) are the regression coefficients of the meteorological variables, and \(b\) is the intercept.

The principal factors of change in PET between separate periods can be obtained by the equation:

\[
\Delta \text{PET} = a_1 \Delta x_1 + a_2 \Delta x_2 + a_3 \Delta x_3 + \cdots + a_n \Delta x_n
\]

where \(\Delta x_1, \ldots, \Delta x_n\) are the trend slopes for each of the meteorological variables, and \(\Delta \text{PET}\), the calculated trend, represents the sum of the contributions of each meteorological variable. The contributions of the meteorological variables \((a_1 \Delta x_1, \ldots, a_n \Delta x_n)\) to change in PET are the product of the meteorological variable trend and the regression coefficient for each meteorological variable [13]. The veracity of this method is tested statistically by comparing \(\Delta \text{PET}\) against the PET trends (\(T_{\text{PET}}\)).

In order to evaluate and draw the relative changes of each climatic element against the corresponding relative changes of the PET, a simple but practical method, sensitivity analysis
recommended by many previous researchers [7, 11, 16] was chosen in this study. 

\[ S_{V_i} = \lim_{\Delta V_i \to 0} \left( \frac{\Delta PET}{\Delta V_i} \right) = \frac{\partial PET}{\partial V_i} \cdot \frac{V_i}{PET} \]  

(4)

where \( S_{V_i} \) denotes the sensitivity coefficient, and \( i \) denotes the \( i \)th variable. A positive (or negative) coefficient represents an upward trend in PET (or decrease) as the climatic variable increase. Assuming all other meteorological variable are constant, if the \( S_{V_i} \) equals 0.2, 10% increase in meteorological variable would result in a 2% increase in PET. The greater the \( S_{V_i} \), the higher sensitivity of PET to \( V_i \) is expected [16]. In this study, sensitivity coefficients were computed with daily meteorological data. Annual and seasonal average sensitivity coefficients were obtained by averaging daily values.

3 Results

3.1 Spatiotemporal characteristics of PET

Multiyear mean annual PET from 1970 to 2020 was 872 mm for the entire study area (Table 1). Annual PET showed a significant increasing trend with a rate of 0.78 mm/year (\( p < 0.05 \)). Seasonal variation in PET was also examined in the current study. Multiyear average summer PET had the highest value (369 mm), followed by spring (253 mm), autumn (165 mm) and winter (85 mm). There was an upward trend in PET in all seasons during 1970–2020. Autumn and winter conditions both produced a statistically significant upward trend in PET (\( p < 0.05 \)) as well as an increasing slope with respective gradients of 0.12 and 0.11 mm/year.

Seasonal PET trends were calculated for each station to show spatial variation in PET (Fig 2 and Table 2). PET did not vary uniformly across the study area in different seasons. Although summer PET exhibited an increasing trend from 1970 to 2020, 35 stations showed negative trends in summer PET, 11 of which were significant decreases. This phenomenon implied that consideration only of average regional PET is inadequate to reveal the mechanisms that triggered PET variation. Of the 56 sites analyzed, 18 sites exhibited significant positive PET trends (\( p < 0.05 \)) in autumn and 12 in spring, whereas significant negative trends (\( p < 0.05 \)) were observed in only three sites in autumn and seven in spring. The greatest number of sites with increasing PET trends was found in winter (about 75% of all sites); 15 sites were statistically significant (\( p < 0.05 \)).

Multiyear average PET across the entire SC-CQ region in 1970–2020 ranged from 600 to 1200 mm. The annual distribution showed a coherent spatial pattern, with a relatively low value in the north of the study area and a relatively high value toward the south (Fig 3(A)). The trends for annual PET at 56 stations in the period 1970–2020 are shown in Fig 3(B). Annual PET showed a positive trend at 33 stations (58.9%), mainly in the northern part of the area; the trend was significant at 12 stations at a 95% confidence level. A negative trend in PET was found at 23 stations (41.1%); the trend was statistically significant at eight stations (14.3%) at a 95% confidence level. Change in PET exhibited an uneven distribution, which indicated that PET variation was arose from the combined effect of meteorological elements.

| Spring | Summer | Autumn | Winter | Annual |
|--------|--------|--------|--------|--------|
| Average value (mm) | 253 | 369 | 165 | 85 | 872 |
| Trend slope (mm/year) | 0.17 | 0.07 | 0.12 * | 0.11 * | 0.78 * |

Note: * indicates the 0.05 significance level.
3.2 Spatiotemporal characteristics of basic meteorological factors

The same trend analysis was conducted at both annual and seasonal scales to identify the trigger mechanisms of PET variation. Wind speed ($W_s$), air temperature ($T_a$), relative humidity (RH), net radiation ($R_n$) and vapor pressure deficit (VPD) were analyzed in this study (Figs 4–7). Mean annual $T_a$ and mean annual RH had fairly similar spatial distributions, with a clear difference between east and west and decreasing from the southeast to the northwest (Fig 4). Mean annual $R_n$ showed a clear southwestern–northeastern high-low gradient. Compared with other meteorological variables, mean annual VPD and mean annual $W_s$ showed complex spatial patterns. Relatively low mean annual VPD and mean annual $W_s$ values were primarily scattered in northwestern and northeastern areas of the SC-CQ region.

Annually, spatial trends for five meteorological variables were also identified in this study (Fig 5). Positive trends of mean annual VPD were found across the entire study area except for

Table 2. Numbers of stations with different trends of potential evapotranspiration by season.

|                  | Spring | Summer | Autumn | Winter | Annual |
|------------------|--------|--------|--------|--------|--------|
| Significant positive trend ($p < 0.05$) | 12     | 4      | 18     | 15     | 12     |
| Nonsignificant positive trend                  | 26     | 17     | 23     | 26     | 21     |
| Significant negative trend ($p < 0.05$)      | 7      | 11     | 3      | 4      | 8      |
| Nonsignificant negative trend                  | 11     | 24     | 12     | 11     | 15     |

Fig 2. Seasonal trends of potential evapotranspiration at each station during 1970–2020. The columns are scaled according to the magnitude of the trend. The upward and downward columns denote increasing and decreasing tendencies, respectively.

https://doi.org/10.1371/journal.pone.0268702.g002
some negative trends at a few isolated sites. A similar pattern was found in the annual $T_a$. Over 85% of the sites showed a positive trend for annual $T_a$ ($p < 0.05$), most of which (>50% of all stations) were statistically significant. This result suggests the general sharp warming in the study area, which is in line with the global warming trend detected in many areas of the world. Annual $R_n$ and annual RH were characterized by negative trends across the study area except at a few sites. Changes of annual $W_s$ had strong spatial variabilities. An upward trend was

![Spatial distributions of (a) mean annual PET, and (b) its trends slopes and the MK test results ($p < 0.05$) in the Sichuan-Chongqing region for 1970–2020. Blue upward and red downward triangles represent positive and negative trends, respectively. Solid triangles indicate trends are statistically significant ($p < 0.05$).](https://doi.org/10.1371/journal.pone.0268702.g003)

![Mean annual values of five basic meteorological variables ((a) vapor pressure deficit, (b) net radiation, (c) relative humidity, (d) air temperature and (e) wind speed) at each station in the Sichuan-Chongqing region from 1970 to 2020. Republished under a CC BY license, with permission from the China Meteorological Data Service Center, original copyright 2005–2017.](https://doi.org/10.1371/journal.pone.0268702.g004)
found mainly in the east of the study area and a downward trend was found in the western and central areas.

Seasonally, the spatial distributions of trends of the five meteorological factors are shown in Fig 6. The percentages of stations showing statistically significant trends ($p < 0.05$) for these variables are displayed in Fig 7. The overall impression was that the changing direction of
seasonal meteorological factors and their distributions were generally consistent with those at
the annual scale, shown in Fig 5. Seasonal and annual average VPD both showed a significant
positive trend at most stations. Significant negative trends of VPD were not detected in spring
and autumn. Rather weak change trends were found in the northwest of the study area.

The number of stations with statistically significant negative trends in $R_n$ were considerably
more numerous than that with statistically significant positive trends. Annually average $R_n$
showed a significant negative trend for 31 stations (55% of all stations). In seasonal distributions,
the maximum number of significantly decreasing trends in average $R_n$ was found in the summer.
Compared with other meteorological factors, there was no clear seasonal variation in RH between
different stations, even though some stations showed statistically significant change trends.

The warming trends for both seasonal and annual $T_a$ were overwhelming, and most sites
showed a significant increasing trend ($p < 0.05$). Winter $T_a$ had the largest trend slopes when
compared to other seasons. In contrast with $T_a$, both annual and seasonal $W_s$ showed a signifi-
cant decreasing trend at most stations. Stations that showed a negative trend in $W_s$ were
mainly in the western part of the study area.

In general, on both an annual and a seasonal basis, trends in these basic meteorological fac-
tors were spatially very variable. However, a dominance of downward trends in $R_n$ and $W_s$, 
and upward trends in $T_a$ and VPD could be seen in this region. Average RH showed a spatial
mix of increasing and decreasing trends both annually and seasonally, with more apparent
downward trends.

### 3.3 Dominant meteorological factors

#### 3.3.1 Quantitative PET contribution analysis.

The contributions of different driving fac-
tors using stepwise regression and compared the impacts of different factors for each

![Fig 7. Percentage of stations with significant trends ($p < 0.05$) for five basic meteorological variables ((a) vapor pressure deficit, (b) net radiation, (c) relative humidity, (d) air temperature and (e) wind speed) at annual and seasonal scales.](https://doi.org/10.1371/journal.pone.0268702.g007)
A meteorological station were investigated in the study area. The coefficient of determination \(R^2\) between \(\Delta PET\) and \(T_{PET}\) was 0.9. This high correlation implied that stepwise regression was able to identify the effects of the meteorological factors on PET trends. Fig 8 displayed the contributions of five meteorological elements (VPD, \(R_n\), RH, \(T_a\) and \(W_s\)) to the mean annual PET trends and the spatial distribution of their importance.

1. VPD had motivated efforts to annual PET change for almost all stations, with contribution value ranging from \(-0.4\) to \(2.5\) mm/year. The center of Chongqing province and center and northwest of Sichuan province achieved relatively greater contribution value.
2. \(R_n\) was strongly related to PET at an annual scale (average contributions varied from \(-1.8\) to \(1.2\) mm/year). The contributions of \(R_n\) on PET on an annual scale were negative for most stations.
3. The contributions of RH on PET were close to zero for more than half of the stations, which indicates that changing effects of RH on annual PET were weakened for this study area when compared to other climatic factors.
4. The station to station variability of contribution of \(T_a\) on PET trend was in the range of \(0\) to \(1.1\) mm/year. One salient feature was that the contributions of \(T_a\) to PET on the periphery of the study area were relatively high.
5. The positive annual contributions of \(W_s\) to PET were mainly distributed in the eastern part of the study area and negative contributions were mainly found in the western region. Contributions of annual \(W_s\) to PET were in the range \(-2\) to \(1.4\) mm/year. Over the entire region, the contributions of decreased \(W_s\) and \(R_n\) were balanced by increased \(T_a\) and VPD, leading to increased PET.

Fig 9 presents the spatial distribution of the leading meteorological factors of PET, and Table 3 lists the numbers of stations at which a particular climatic factor was dominant at annual and seasonal scales. In terms of annual effects, the distribution of climate factors varied spatially (Fig 9). Given that VPD caused changes in PET at 27 stations (close to 50%), it was regarded to be most strongly associated with the variation in annual PET (Fig 10). Changes in annual PET in the center and west of the study area were mainly contributed to VPD and \(W_s\).
dominated changes in annual PET was observed in the east of the study area. VPD was the major driver of increasing PET trends, followed by $W_s$. $W_s$ was the major driver of decreasing PET trends, followed by $R_n$. In contrast to the other four meteorological factors, RH had little effect on annual PET across the SC-CQ region.

In seasonal terms, the dominant factor contributing to changes in PET varied across stations. There were clear regional differences in spring. $W_s$ was the dominant factor in the northwest. VPD was the dominant factor in the southeast. In summer, $R_n$ was the factor most strongly associated with decreased PET, and VPD was mainly responsible for increased PET. Summer PET was greatly affected by changes in $R_n$, followed by VPD and $W_s$. In autumn, stations at which VPD was the dominant driver of PET were located mainly in the central–western area, and those at which $R_n$ was the dominant driver were located mainly in the eastern area. In winter, VPD had the strongest positive effect on PET, and $W_s$ mainly controlled the decrease in PET. Stations at which VPD or $W_s$ were dominant factors were widely dispersed across the study area. VPD had an overwhelmingly dominant effect on the increase in PET at most stations in most seasons, and RH contributed least. Except in summer, $W_s$ was generally the dominant driver for inducing the decreasing PET trend.

Table 3. Number of stations with dominant factors of PET trends at annual and seasonal scales during 1970–2020.

| Time scale | VPD | $R_n$ | RH | $T_a$ | $W_s$ |
|------------|-----|------|----|------|------|
| Annual     | 27  | 9    | 0  | 2    | 18   |
| Spring     | 27  | 13   | 0  | 1    | 15   |
| Summer     | 14  | 25   | 1  | 4    | 12   |
| Autumn     | 26  | 13   | 0  | 1    | 16   |
| Winter     | 32  | 1    | 0  | 1    | 22   |

https://doi.org/10.1371/journal.pone.0268702.t003
3.3.2 Quantitative PET sensitivity analysis. To better understand the influence of climatic variables on the PET trend, the sensitivity analysis of the PET to climatic variables was performed. The averaged sensitive coefficients of PET to five basic meteorological variables of all observation sites are shown in Table 4 and the spatial patterns of the relative sensitivity of the PET to five basic meteorological elements are displayed in Fig 11. The combination of Table 4 and Fig 11 explains the result of sensitivity analysis. Annual and seasonal PET were positively correlated with $T_a$, $R_n$, VPD, and $W_s$ and negatively correlated with RH (Table 4), indicating an increase (or decrease) in PET as the meteorological factors increase (or decrease) except for RH. On a full-year basis, although the spatial pattern of the relative sensitivity illustrated that the PET response to changes in each meteorological factor was different from site to site. $R_n$ and RH were the two most sensitive elements on annual PET throughout the whole study region in general, followed by VPD. The least sensitive variable was $W_s$. The highest absolute sensitivity coefficient was computed for $T_a$ (0.19), VPD (0.29), $R_n$ (0.85), RH (0.70) and $W_s$ (0.15) in summer, winter, summer, winter and winter, respectively. The most sensitive

Fig 10. Dominant factors are shown as percentages for stations with negative, positive, significantly negative ($p < 0.05$) and significantly positive ($p < 0.05$) trends of PET in (a) annual, (b) spring, (c) summer, (d) autumn and (e) winter.

https://doi.org/10.1371/journal.pone.0268702.g010

Table 4. The sensitivity coefficient of the potential evapotranspiration to the five basic meteorological variables.

| Time scale | $S_{T_a}$ | $S_{VPD}$ | $S_{R_n}$ | $S_{RH}$ | $S_{W_s}$ |
|------------|-----------|-----------|-----------|----------|----------|
| Annual     | 0.14      | 0.21      | 0.78      | −0.6     | 0.10     |
| Spring     | 0.13      | 0.23      | 0.75      | −0.53    | 0.09     |
| Summer     | 0.19      | 0.14      | 0.85      | −0.49    | 0.05     |
| Autumn     | 0.16      | 0.19      | 0.80      | −0.69    | 0.09     |
| Winter     | 0.06      | 0.29      | 0.63      | −0.70    | 0.15     |

Note: $S_{T_a}$, $S_{VPD}$, $S_{R_n}$, $S_{RH}$ and $S_{W_s}$ denote the sensitivity coefficient of potential evapotranspiration to air temperature ($T_a$), vapor pressure deficit (VPD), net radiation ($R_n$), relative humidity (RH) and wind speed ($W_s$), respectively.

https://doi.org/10.1371/journal.pone.0268702.t004
variable on spring (0.75), summer (0.85) and autumn (0.80) PET was $R_n$. During winter, the greatest sensitivity of PET was for RH ($-0.70$).

4 Discussion

4.1 PET trend

Various studies have quantified PET trends in many regions over different periods [13, 15, 18, 37]. Most studies, however, have focused on regional average PET trends and taken no account of the spatial distribution of PET. In a large region with unique weather conditions and complex topography like the SC-CQ region, long-term trends in annual and seasonal PET and its primary driving mechanisms were inevitably spatially variable, which have not been fully analyzed in published research [15]. We examined the regional diversity of the PET in the SC-CQ region during 1970–2020. It can be found from the above analysis that there were complex spatial patterns in the PET and its change. Overall, at almost 60% of the meteorological stations in the region, mainly distributed in the north, annual average PET showed a positive increasing trend (Fig 3(B)). Similar to our study, high spatiotemporal heterogeneity in PET has also been found in the Yellow River basin [15] and the Beijing-Tianjin Sand Source Control Project region [12], both of which are large regions in China.

Some studies have found that PET showed a distinct negative trend along with significantly increasing $T_a$, and identified this phenomenon as an evaporation paradox. In the SC-CQ region, on a seasonal scale, more sites showed an increasing trend than a decreasing trend, except in summer, which confirmed the existence of the evaporation paradox generally in the months of summer. On a regional scale, the evaporation paradox phenomenon occurred more frequently in the southern Sichuan-Chongqing region during 1970–2020. Similar findings reported an evaporation paradox accompanied by the simultaneous PET decrease and $T_a$ rise within China (e.g. Yangtze River catchment [38] and Beijing-Tianjin region [12] and some other regions worldwide [39, 40]. Another form of the evaporation paradox expressed by a
declined $T_a$ and an elevated PET was also reported by previous studies [41]. A possible explanation of these two forms of the evaporation paradox is that the increased $T_a$ and the decreased $W_s$ or sunshine duration have the first role in the PET reduction and the increased atmospheric demand mainly cause the increase of PET. These spatial and regional differences of the PET response to meteorological variables need further investigation.

4.2 Meteorological factors of PET variation

4.2.1 Contribution and sensitivity of PET to the change of meteorological factors.

Long-term trends of annual and seasonal PET are directly influenced by the combined effects of changes in meteorological variables such as wind speed, radiation and humidity [1, 7]. The individual contribution of climate factors to PET was identified in the current study. Decreases in $W_s$ and $R_n$ and increase in VPD greatly affected the changing direction of PET. The results we obtained that identified the factors having the most effect on PET are generally consistent with those from previous studies of other regions, such as Siberian river basins [11] and the Qinhua River basin [3, 4]. Spatial distributions of driving factors were complex in the study region (Fig 9). Differences across the region were primarily due to the study area being large and having a complex topography and a heterogeneous climate. Similar characteristics have been studied in many parts of China, such as the Yellow River basin [15], the Yangtze River basin [38], and the Haihe River basin [1].

In order to further quantitatively assess the variability of PET to the changes in the controlling meteorological factors across the entire study area, conducting sensitivity of PET to meteorological elements at annual and seasonal scales is necessary. The positive sensitivity coefficient for $T_a$, VPD, $R_n$ and $W_s$ indicated the PET increases with the increase of these meteorological elements, while the negative sensitivity coefficient for RH implied the PET increases with the decrease of RH (Table 4). PET was highly sensitive to $R_n$ and RH relative to the other basic meteorological variables in this study area. The results of sensitivity analysis in this study are close to the previous fundings. Numerous studies concluded that RH was the most sensitive factor on PET in southwest China [42], Yellow River Basin [15] and coastal southern Iran [16]. Xu et al. (2006) indicated that PET was most sensitive to the $R_n$, followed by RH, air temperature and $W_s$ in Yangtze catchment. $R_n$ and RH were considered as the most-second sensitive factor in Qilian Mountains, northwestern China [43]. The differences of the most sensitive variable existed in some regions, e.g., Guo et al. (2017) found that air temperature had the highest sensitivity in Australia.

Averaged across all meteorological stations, the greatest and lowest sensitivity coefficient of PET to $T_a$ ($S_{T_a}$) was found in summer (0.19) and winter (0.06), respectively. It is in agreement with our common sense that the warmer the $T_a$ is, the more the sensitivity of PET to $T_a$ is [15]. Additionally, our results addressed that $W_s$ appeared to cause minor perturbation in PET change in the study area. However, the current studies conducted in the arid region revealed that the sensitivity of PET to $W_s$ was considerable [16, 40]. The difference may be attributed to the different climates in the study area.

The impacts of meteorological factors were dependent not only on the sensitivity of PET to meteorological factors, but also on the change magnitude of meteorological factors [15, 38, 42]. Although RH exhibited high sensitivity to PET at annual and seasonal scales, it had little effect on variation in PET during the study period because of its much smaller change magnitude relative to other climatic elements. Similar to fundings by Xu et al. (2006), they proposed that RH produced little contribution to changing PET, despite it was the most sensitive variable in the Yangtze River catchment. Moreover, a relatively low $S_{W_s}$ was found in the SC-CQ region, while changes in $W_s$ were found to play a significant role in the PET changing as the
W_s of most stations showed a significant trend (Fig 5). The VPD was one of the driving factors affecting the PET variation because it was not only the sensitive variable, but also a variable with a significant positive trend at most stations across the whole study region. Presenting sensitivity and contribution of meteorological elements to PET simultaneously not only can avoid uncertainties from a single approach, but also provide comprehensive interpretation for PET dynamic over this region [15].

### 4.2.2 Impacts of meteorological factors on trends of PET

The globally warming climate has accelerated the water cycle, which has further increased terrestrial PET [5, 17, 44]. In our study, T_a showed increasing trends in the entire study period and winter T_a had the largest trend slopes for most stations, which is consistent with the persistent warming in winter currently observed in China [15]. T_a has increased globally in response to the increase in atmospheric greenhouse gases [14], increased haze formation [29, 45], and increased cloud cover [3]. Some studies have identified significant heat island effects in SC-CQ due to urban development [46]. The complex topography makes the local climate more responsive to land surface changes and increased pollution emissions [29], and so the increase in T_a in this region was inevitable. However, an increase in T_a was not the primary driver of the increase in PET in all cases. T_a had much less effect on annual and seasonal PET than W_s, VPD or R_n for most stations in SC-CQ. Similar results have been obtained in many previous studies of other regions worldwide [3, 12, 37, 40]. However, Darshana et al. (2013) used sensitivity analysis and found that change in annual PET across the Tons River basin in central India was caused mainly by changes in maximum T_a. The inconsistency between their findings and ours may be due to differences in the study period and study regions.

In a humid atmosphere, solar radiation is the principal source of energy required for evaporation [47]. Thus the decrease in R_n has been considered to be a key driver of the decrease in PET and has been found to be the case for many regions across the world, such as the Taohe River basin [48], the Hai River basin [37], the entire northern hemisphere [49], and northeast India [39]. A gradual decrease in solar radiation or sunlight duration is likely caused by increased air pollution [47] and change in W_s [50]. Increased levels of aerosols from contaminants have resulted in increased cloud cover, which had a negative effect on sunshine duration and available solar radiation [51]. W_s is highly dependent on solar radiation because wind is caused by radiation-induced differences in surface temperature [50]. Thus, interactions between W_s and aerosols have a strong effect on radiation, and then drive changes in PET.

For the whole study area, W_s was a substantial factor affecting the PET trend, particularly in spring and winter. Other research has also attributed the decreased PET to W_s, for example in the Jing River basin [7], the Qinhuai River basin [3], an arid region of China [14], and northeast India [39], among other regions. Annual and seasonal W_s showed decreasing trends at most sites during 1970–2020 (Figs 5 and 6), which suggests a weakening of the East Asian monsoon in the SC-CQ region. The reduction of W_s can be greatly induced by various causes including regional and global warming [52, 53], human-induced factors [4, 5, 54], and changes in atmospheric circulation patterns [7]. Under the background of vigorously developing western China, SC-CQ has thus experienced extensive rapid urbanization and population growth in recent decades [25]. Some studies have suggested that a decrease in W_s was at least partially correlated to an increase in surface roughness caused by human activity [13, 55]. It has been suggested that the reduced surface pressure gradient between high and low latitudes in southwest China might be a reason for decreased W_s [56]. The issue of what drives change in W_s is clearly complex, and so the cause of the decrease in W_s across SC-CQ needs more investigation.

Increased VPD was the major driver of change in PET at all time scales. Increase in VPD countered the effects of decreases in W_s and R_n on PET, leading to a positive PET trend across
the entire study area. VPD appears to have been the principal factor in increasing the rate of moisture cycling and evapotranspiration. Atmospheric water demand, which is closely related to VPD, was also responsible for the change in PET in this region [3, 44, 57]. Our results are consistent with those obtained by Qin et al. (2019), Tang et al. (2021), and Abtew et al. (2011), which respectively show that VPD was a dominant climate factor of increased PET in southern China, Siberian river basins, and southern Florida. Hao et al. (2018) found that VPD was positively correlated with $T_a$ and negatively correlated with RH in a wet region. These results suggest that the increasing PET trend may be more rapid for humid areas, where increasing $T_a$ and decreasing atmospheric humidity induce increase in VPD. Researchers worldwide have recently become more interested in the effects of change in VPD [19, 40, 44]. Vast quantities of research highlighted the elevating VPD and the consequent increased PET have identified significant effects on the water cycle [40] and the carbon cycle [57], which can potentially exacerbate water stress and existing urban heat island effects [44, 58].

4.3 Deficiencies of this study

This study examined the spatio-temporal pattern of the PET as well as of the climatic elements that affect PET in the Sichuan-Chongqing region from 1970 to 2020. However, its main drawbacks include:

1. Long-term weather data gathered from meteorological observation sites for calculating PET have been widely used in similar studies [5, 12, 16, 38]. The strength of the observational data at certain sites is that it may reflect the influence of local climate effects. However, it may not represent the spatial variability of weather over a large study area due to the density of weather stations. Gridded weather data provide more comprehensive climate information, and they have been used for estimating PET within the whole region recently [59]. It should be noted that some researchers maintained that gridded weather data sets could overestimate PET results, especially in well-watered surface, owing to the chronic overstatement of $T_a$ and $W_s$ and understatement of air humidity [59–61]. The selection of different data sets for the regional-scale PET evaluation would have an impact on the results. Future studies can be carried out to estimate trends of PET and its driving factors using the gridded datasets, and evaluate the performance of gridded and weather station data.

2. In addition to the five basic meteorological factors analyzed in this paper, some other variables (e.g. sky cover and sunlight duration) can indirectly affect the spatio-temporal pattern of the PET trend [1, 13, 54]. Future studies should be further explored these parameters as major controlling factors to fully account for PET change.

5 Conclusions

The FAO-56 Penman–Monteith model was adopted to analyze long-term (1970–2020) PET time series data. The contributions of variation in net radiation ($R_n$), wind speed ($W_s$), air temperature ($T_a$), vapor pressure deficit (VPD) and relative humidity (RH) to the PET trend were quantitatively assessed in 56 stations across the Sichuan-Chongqing region over the past 51 years. The PET sensitivity to these meteorological variables was also estimated in this study. Key findings from this study are summarized as follows.

1. Seasonal and regional differences in PET and their associated meteorological variables are bound to exist. There was a positive trend in PET for more than 58% stations at annual scale. Approximately 68%, 38%, 73% and 73% of all surveyed weather stations produced an increasing trend in PET during spring, summer, autumn and winter, respectively. The
annual $W_s$ trend across the study area varied spatially, with a negative trend in the east of the study area and a positive trend in the west and center. Most stations showed increasing trends in $T_a$ and VPD, and decreasing trends in $W_s$ and $R_n$ on an annual scale. Annual RH showed a mixture of increasing and decreasing trends spatially, with the decreasing trends being stronger. Spatial heterogeneity was also observed in the seasonal trends of meteorological variables.

2. Climate change has greatly impacted local hydrology. Contribution analysis showed that $W_s$ was the primary controlling factor in PET in annual, spring, autumn and winter, and $R_n$ was the primary influence in summer for stations with a negative PET trend. VPD was the dominant factor in all time scales for stations with a positive PET trend. The positive effects of VPD offset the negative effects of $W_s$ and $R_n$, leading to increased PET for the entire study area. Sensitivity analysis revealed that annual and seasonal PET were positively correlated with all climatic variables except for RH. PET was mostly sensitive to RH and $R_n$. The results from the contribution approach did not coincide with those of the sensitivity analysis. A comparative analysis illustrated that the effects of meteorological factors are influenced by not only the sensitivity of PET to meteorological factors but also the change magnitude of the meteorological factors.

3. The distinct seasonal and regional characteristics of changes in PET and their causes showed the importance of estimating the hydro-meteorological processes at fine spatiotemporal resolution. VPD and $R_n$ as the main causes of PET changing must be taken into account for the water cycle and local natural resources in an area of climate change and intense human activity.

**Supporting information**

S1 File.

(XLSX)

**Acknowledgments**

We acknowledge the China Meteorological Data Service Center (http://www.cma.gov.cn/) for providing daily weather observation data and the Computer Network Information Center (http://www.gscloud.cn/) for sharing the digital elevation model (DEM) and boundary of the Sichuan-Chongqing region.

**Author Contributions**

**Conceptualization:** Qingzhou Zheng, Jun He.

**Data curation:** Jun He.

**Formal analysis:** Mengsheng Qin, Xia Wu, Tiantian Liu, Xiaolin Huang.

**Funding acquisition:** Jun He.

**Investigation:** Qingzhou Zheng, Jun He, Xia Wu.

**Methodology:** Qingzhou Zheng, Xia Wu.

**Project administration:** Jun He.

**Resources:** Qingzhou Zheng, Jun He.
Software: Qingzhou Zheng, Mengsheng Qin, Xiaolin Huang.

Supervision: Xia Wu, Tiantian Liu.

Validation: Xia Wu, Tiantian Liu.

Visualization: Qingzhou Zheng, Mengsheng Qin, Xiaolin Huang.

Writing – original draft: Qingzhou Zheng, Jun He.

Writing – review & editing: Qingzhou Zheng, Jun He, Mengsheng Qin, Xia Wu, Xiaolin Huang.

References

1. Abtew W, Obeysekera J, Iricanin N. Pan evaporation and potential evapotranspiration trends in South Florida; Hydrological Processes. 2011; 25(6): 958–969.

2. Allen R, Pereira L, Raes D, Smith M. Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56; Fao, Rome. 1998; 300(9): D05109.

3. Beven K. A sensitivity analysis of the Penman-Monteith actual evapotranspiration estimates; Journal of Hydrology. 1979; 44(3–4): 169–190.

4. Blankenau P A, Kilic A, Allen R. An evaluation of gridded weather data sets for the purpose of estimating reference evapotranspiration in the United States; Agricultural Water Management. 2020; 242: 106376.

5. Chen D, Gao G, Xu C, Guo J, Ren G. Comparison of the Thornthwaite method and pan data with the standard Penman-Monteith estimates of reference evapotranspiration in China; Climate Research. 2005; 28(2): 123–132.

6. Darshana, Pandey A, Pandey R P. Analysing trends in reference evapotranspiration and weather variables in the Tons River Basin in Central India; Stochastic Environmental Research & Risk Assessment. 2013; 27(6): 1407–1421.

7. Feng X, Wei S, Wang S. Temperature inversions in the atmospheric boundary layer and lower troposphere over the Sichuan Basin, China: Climatology and impacts on air pollution; Science of the Total Environment. 2020; 726: 138579. https://doi.org/10.1016/j.scitotenv.2020.138579 PMID: 32305769

8. Gao G, Xu C, Chen D, Singh V. Spatial and temporal characteristics of actual evapotranspiration over Haihe River basin in China; Stochastic environmental research and risk assessment. 2012; 26(5): 655–669.

9. Garrett T J, Zhao C. Increased Arctic cloud longwave emissivity associated with pollution from mid-latitudes; Nature. 2006; 440(7085): 787–789. https://doi.org/10.1038/nature04636 PMID: 16598255

10. Guo J, Han G, Xie Y, Cai Z, Zhao Y. Exploring the relationships between urban spatial form factors and land surface temperature in mountainous area: A case study in Chongqing city, China; Sustainable Cities and Society. 2020; 61: 102286.

11. Han S, Di X, Wang S. Decreasing potential evaporation trends in China from 1956 to 2005: Accelerated in regions with significant agricultural influence?; Agricultural & Forest Meteorology. 2012; 154: 44–56.

12. Hao L, Huang X, Qin M, Liu Y, Li W, Sun G. Ecological processes explain urban dry island effects in a wet region, southern China; Water Resources Research. 2018; 54(9): 6757–6771.

13. Hao L, Sun G, Liu Y, Wan J, Qin M, Qian H, et al. Urbanization dramatically altered the water balances of a paddy field dominated basin in Southern China; Hydrology and Earth System Sciences. 2015; 12 (7): 3319–3331.

14. Huang X, Hao L, Sun G, Yang Z L, Li W, Chen D. Urbanization Aggravates Effects of Global Warming on Local Atmospheric Drying; Geophysical Research Letters. 2021; e2021GL095709.

15. Irmak S, Kabenge I, Skaggs K E, Mutibwa D. Trend and magnitude of changes in climate variables and reference evapotranspiration over 116-yr period in the Platte River Basin, central Nebraska–USA; Journal of Hydrology. 2012; 420: 228–244.

16. Jhajharia D, Dinapashoh Y, Kahya E, Singh V P, Fakheri-Fard A. Trends in reference evapotranspiration in the humid region of northeast India; Hydrological Processes. 2012; 26: 421–435.

17. Jiang S, Chen X, Smettem K, Wang T. Climate and land use influences on changing spatiotemporal patterns of mountain vegetation cover in southwest China; Ecological Indicators. 2021; 121: 107193.
18. Jiang S, Liang C, Cui N, Zhao L, Du T, Hu X, et al. Impacts of climatic variables on reference evapotranspiration during growing season in Southwest China; Agricultural Water Management. 2019; 216: 365–378.
19. Kendall M G. Rank correlation methods; British Journal of Psychology. 1990; 25(1): 86–91.
20. Lewis C S, Geli H M, Neale C M. Comparison of the NLDAS weather forcing model to agrometeorological measurements in the western United States; Journal of Hydrology. 2014; 510: 385–392.
21. Li X, He B, Quan X, Liao Z, Bai X. Use of the standardized precipitation evapotranspiration index (SPEI) to characterize the drying trend in southwest China from 1982–2012; Remote Sensing. 2015; 7(8): 10917–10937.
22. Lu J, Sun G, McNulty S, Amatya. “A Comparison of Six Potential Evapotranspiration Methods for Regional Use in the Southeastern United States.”; Journal of the American Water Resources Association. 2005; 41: 621–633.
23. Mann H B. Nonparametric Tests Against Trend; Econometrica. 1945; 13(3): 245–259.
24. Monteith J L. Evaporation and environment. The stage and movement of water in living organisms; Symp.soc.exp.biol.the Company of Biologists. 1965.
25. Moorhead J, Gowda P, Hobbins M, Senay G, Paul G, Marek T, et al. Accuracy assessment of NOAA gridded daily reference evapotranspiration for the Texas High Plains; JAWRA Journal of the American Water Resources Association. 2015; 51(5): 1262–1271.
26. Newman B D, Wilcox B P, Archer S R, Breshears D D, Dahm C N, Duffy C J, et al. Ecohydrology of water-limited environments: A scientific vision; Water resources research. 2006; 42(6).
27. Nouri M, Homaei M, Bannayan M. Quantitative trend, sensitivity and contribution analyses of reference evapotranspiration in some arid environments under climate change; Water Resources Management. 2017; 31(7): 2207–2224.
28. Peng F, You Q, Xue X, Guo J, Wang T. Evapotranspiration and its source components change under experimental warming in alpine meadow ecosystem on the Qinghai-Tibet plateau; Ecological Engineering. 2015; 84: 653–659.
29. Peng W, Kuang T, Tao S. Quantifying influences of natural factors on vegetation NDVI changes based on geographical detector in Sichuan, western China; Journal of Cleaner Production. 2019; 233: 353–367.
30. Qin M, Hao L, Sun L, Liu Y, Sun G. Climatic Controls on Watershed Reference Evapotranspiration Varied during 1961–2012 in Southern China; Journal of the American Water Resources Association. 2019; 55(1): 189–208.
31. Qin M, Zhang Y, Wan S, Yue Y, Zhang B. Impact of climate change on "evaporation paradox" in province of Jiangsu in southeastern China; PLoS ONE. 2021; 16(2): e0247278. https://doi.org/10.1371/journal.pone.0247278 PMID: 33606798
32. Qin T, Yang P, Groves C, Chen F, Xie G, Zhan Z. Natural and anthropogenic factors affecting geochemistry of the Jialing and Yangtze Rivers in urban Chongqing, SW China; Applied Geochemistry. 2018; 98: 448–458.
33. Rodrick, Michael L, Farquhar, Graham D. The Cause of Decreased Pan Evaporation over the Past 50 Years; Science. 2002; 298(5597): 1410–1411. https://doi.org/10.1126/science.1075390 PMID: 12434057
34. Ruirui Y, Xiaolin H, Lu H. Spatio–Temporal Variation of Vapor Pressure Deficit and Impact Factors in China in the Past 40 Years; Climatic and Environmental Research. 2021; 26(4): 413–424.
35. Shan N, Shi Z, Yang X, Gao J, Cai D. Spatiotemporal trends of reference evapotranspiration and its driving factors in the Beijing–Tianjin Sand Source Control Project Region, China; Agricultural and Forest Meteorology. 2015; 200: 322–333.
36. Shen Y, Liu C, Min L, Yan Z, Tian C. Change in pan evaporation over the past 50 years in the arid region of China; Hydrological Processes. 2009; 24(2): 225–231.
37. Sun G, Lockaby B G. Water quantity and quality at the urban–rural interface; Urban–rural interfaces: Linking people and nature. 2012: 29–48.
38. Tang Y, Tang Q. Variations and influencing factors of potential evapotranspiration in large Siberian river basins during 1975–2014; Journal of Hydrology. 2021; 598: 126443.
39. Vautard R, Cattiaux J, You P, Thépaut J-N, Ciais P. Northern Hemisphere atmospheric stilling partly attributed to an increase in surface roughness; Nature geoscience. 2010; 3(11): 756–761.
41. Wang H, Wang L, He J, Ge F, Chen Q, Tang S, et al. Can the GPM IMERG Hourly Products Replicate the Variation in Precipitation During the Wet Season over the Sichuan Basin, China?; Earth and Space Science. 2020; 7(5): e2020EA001090.

42. Wang W, Shao Q, Peng S, Xing W, Tao Y, Luo Y, et al. Reference evapotranspiration change and the causes across the Yellow River Basin during 1957–2008 and their spatial and seasonal differences; Water Resources Research. 2012; 48(5): 113–122.

43. Xu C, Gong L, Jiang T, Chen D, Singh V. Analysis of spatial distribution and temporal trend of reference evapotranspiration and pan evaporation in Changjiang (Yangtze River) catchment; Journal of hydrology. 2006; 327(1–2): 81–93.

44. Xu L, Shi Z, Wang Y, Zhang S, Chu X, Yu P, et al. Spatiotemporal variation and driving forces of reference evapotranspiration in Jing River Basin, northwest China; Hydrological Processes. 2015; 29(23): 4846–4862.

45. Xu Y P, Pan S, Fu G, Tian Y, Zhang X. Future potential evapotranspiration changes and contribution analysis in Zhejiang Province, East China; Journal of Geophysical Research Atmospheres. 2014; 119 (5): 2174–2192.

46. Xu Z, Gong T, Li J. Decadal trend of climate in the Tibetan Plateau—regional temperature and precipitation; Hydrological Processes: An International Journal. 2008; 22(16): 3056–3065.

47. Yang C, Zeng W, Yang X. Coupling coordination evaluation and sustainable development pattern of geo-ecological environment and urbanization in Chongqing municipality, China; Sustainable Cities and Society. 2020; 61: 102271.

48. Yang X, Li Z, Feng Q, He Y, An W. The decreasing wind speed in southwestern China during 1969–2009, and possible causes; Quaternary International. 2012; 263: 71–84.

49. Yang Y, Chen R, Song Y, Han C, Liu J, Liu Z. Sensitivity of potential evapotranspiration to meteorological factors and their elevational gradients in the Qilian Mountains, northwestern China; Journal of Hydrology. 2019; 568: 147–159.

50. Yang Y, Ni C, Jiang M, Chen Q. Effects of aerosols on the atmospheric boundary layer temperature inversion over the Sichuan Basin, China; Atmospheric Environment. 2021; 262: 118647.

51. Zhang S, Tao F, Zhang Z. Spatial and temporal changes in vapor pressure deficit and their impacts on crop yields in China during 1980–2008; Journal of Meteorological Research. 2017; 31(4): 800–808.

52. Zhang Y, Qin B, Chen W. Analysis of 40 year records of solar radiation data in Shanghai, Nanjing and Hangzhou in Eastern China; Theoretical and Applied Climatology. 2004; 78(4): 217–227.

53. Zhang Y, Xue M, Zhu K, Zhou B. What Is the Main Cause of Diurnal Variation and Nocturnal Peak of Summer Precipitation in Sichuan Basin, China? The Key Role of Boundary Layer Low-Level Jet Inertial Oscillations; Journal of Geophysical Research Atmospheres. 2019; 124(5): 2643–2664.

54. Zhao N, Zeng X, Sun H. Impact of global dimming on reference evapotranspiration in Hai River basin, China; Proceedings of the International Association of Hydrological Sciences. 2015; 368: 287–292.

55. Zhao R, Wang H, Chen J, Fu G, Zhan C, Yang H. Quantitative analysis of nonlinear climate change impact on drought based on the standardized precipitation and evapotranspiration index; Ecological Indicators. 2021; 121: 107107.

56. Zheng Q, Hao L, Huang X, Sun L, Sun G. Effects of urbanization on watershed evapotranspiration and its components in southern China; Water. 2020; 12(3): 645–667.

57. Zheng X, Yang C, Zhao T, Luo Y, Duan C, Chen J. Long-term trends in sunshine duration over Yunnan-Guizhou Plateau in Southwest China for 1961–2005; Geophysical Research Letters. 2008; 35(15).

58. Zhou J, Zhao X, Wu J, Huang J, Qiu D, Xue D, et al. Wind speed changes and influencing factors in inland river basin of monsoon marginal zone; Ecological Indicators. 2021; 130: 108089.

59. Zipper S C, Schatz J, Kucharik C J, Loheide S P. Urban heat island-induced increases in evapotranspirative demand; Geophysical Research Letters. 2017; 44(2): 873–881.

60. Zuo D, Xu Z, Yang H, Liu X. Spatiotemporal variations and abrupt changes of potential evapotranspiration and its sensitivity to key meteorological variables in the Wei River basin, China; Hydrological Processes. 2012; 26(8): 1149–1160.