Changes in reference evapotranspiration over China during 1960–2012: Attributions and relationships with atmospheric circulation

Rongfan Chai1,2 | Shanlei Sun1 | Haishan Chen1,2 | Shujia Zhou1,2

1Key Laboratory of Meteorological Disaster, Ministry of Education (KLME)/International Joint Research Laboratory of Climate and Environment Change (ILCEC)/Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters (CIC-FEMD), Nanjing University of Information Science and Technology (NUIST), Nanjing, China
2School of Atmospheric Sciences, Nanjing University of Information Science and Technology (NUIST), Nanjing, China

Correspondence
Shanlei Sun, Key Laboratory of Meteorological Disaster, Ministry of Education, Nanjing University of Information Science and Technology, Nanjing 210044, China.
Email: ppsunsanlei@126.com

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Abstract
This study investigates reference evapotranspiration (ET0) trends in China from 1960 to 2012 based on the Penman–Monteith equation and gridded meteorological measurements. Under the combined impacts of factors influencing ET0 (i.e., net radiation [RN], mean temperature [TAVE], vapour pressure deficit [VPD], and wind speed [WND]), both seasonal and annual ET0 for the whole China and more than half of the grids decreased over the past 53 years. The attribution analyses suggest that for the whole China, the WND is responsible for annual and seasonal ET0 decreases (excluding summer, where RN is responsible). Across China, the annual cause of WND with the largest spatial extent (43.1% of grids) mainly derives from north of the Changjiang River Basin (CJRB), whereas VPD (RN) as a cause is dispersedly distributed (within and to the south of the CJRB). In summer, RN is dominant in more than half of the grids, but the dominance of VPD and WND accounts for approximately 90% of grids during the remaining seasons. Finally, the correlation coefficients between ET0 and the Atlantic Oscillation (AO), North AO, Indian Ocean Dipole (IOD), Pacific Decadal Oscillation (PDO), and El Niño Southern Oscillation (ENSO) indices with different lead times are calculated. For the whole China, annual and seasonal ET0 always significantly correlate with these indices (excluding the IOD) but with varied lead times. Additionally, near half of the grids show significant and maximum (i.e., the largest one between ET0 and a certain index with a lead time of 0–3 seasons) correlation coefficients of ET0 with PDO in spring and summer, ENSO in autumn, and AO in winter. This study is not only significant for understanding ET0 changes, but it also provides preliminary and fundamental reference information for ET0 prediction.

KEYWORDS
attribution analysis, China, climate change, driving forces, reference evapotranspiration, teleconnection indices

1 | INTRODUCTION

Climate change, land use/land cover change, and increased CO2 concentrations have produced profound impacts on both regional and even global hydrological cycles (Milly, Dunne, & Vecchia, 2005; Min, Zhang, Zwiers, & Hegerl, 2011; Mishra et al., 2010; Piao et al., 2007; Zhang, Liu, Zhang, Liang, & Liu, 2016). Accelerated hydrological cycles accompanied with frequent extreme hydrological events (e.g., floods,
droughts, and extreme precipitation) have become a focus of recent climate change studies (Milly, Wetherald, Dunne, & Delworth, 2002; Mishra, Ganguly, Nijssen, & Lettenmaier, 2015; Sheffield & Wood, 2008; Trenberth, 2010; Zhang, Cheng, Zhang, & Liu, 2017). There is a concern that with climate change, droughts may increase in intensity, frequency, area, and duration (Dai, 2013), leading to great impacts on human and natural systems and providing an intense reminder of the potential consequences of droughts. Recently, based on the close relationship between drought and precipitation (Heim, 2002), numerous studies have completely explained drought mechanisms across the globe (Buttafuoco, Caloiero, & Coscarelli, 2015; Schubert et al., 2016; Yan, Zhang, Zhou, & Han, 2017). However, it should be noted that the impacts of evapotranspiration (ET) or reference ET (ET0) have been given less attention, even though they are closely associated with changes in climatic variables and are integrated indicators of climate change. For example, Hu and Willson (2000) and Sun et al. (2016), Sun, Chen, Ju, et al. (2017) have reported that the impact of ET0 on drought could be equivalent to or even higher than that from precipitation. Consequently, understanding the spatial and temporal variations in ET0 is a vital component for comprehensively understanding hydrometeorological changes and is helpful for better monitoring and predicting drought (Beguería, Vicente-Serrano, Reig, & Latorre, 2014; Li, He, Quan, Liao, & Bai, 2015; McEvoy, Huntington, Mejia, & Hobbins, 2016; Sun et al., 2016; Sun, Chen, Sun, et al., 2017; Vicente-Serrano, Beguería, & Lópezmoreno, 2010; Zhang et al., 2018).

Climate change is intensifying and mainly characterized by significant increases in temperature (IPCC, 2014). However, ET0 has not increased with global warming as expected. In contrast, it has shown a decreasing trend in most regions of the world (Roderick & Farquhar, 2002), which is known as the evaporation paradox (Brutsaert & Parlange, 1998). To explain this issue, a number of studies have been performed by quantifying the impacts of meteorological factors on ET0, and they concluded that changes in wind speed and radiation (or sunshine duration) are the main causes of decreased ET0 in some regions (Chen, Liu, & Thomas, 2006; Jhajharia, Dinaposh, Kahya, Singh, & Fakheri-Fard, 2012; Peterson, Golubev, & Groisman, 1995; Roderick, Rotstayn, Farquhar, & Hobbins, 2007; Stanhill & Möller, 2008), whereas water vapour indicators (e.g., relative humidity and vapour pressure deficit) and temperature exert dominant impacts over other regions (Liu, Zheng, Liu, & Cao, 2009; Zhang, Liu, & Hong, 2013). ET0 changes in China have also received considerable attention (Liu, Liu, & Brutsaert, 2018; Liu, Liu, Yang, & Bai, 2016; Liu, Luo, Zhang, & Liu, 2011; Liu & Zhang, 2013; Tang, Tong, Kang, & Zhang, 2011; Wang et al., 2017; Yin, Wu, Gang, & Dai, 2010; Zhang, Ren, Yin, Lin, & Zheng, 2009). It is worth noting that most previous studies have focused on annual ET0 changes. However, seasonal ET0 changes are actually more important for elaborately planning and managing agricultural and water resources. To attribute ET0 changes over China and its subregions, various methods have been proposed and used (e.g., the differential equation method (Zhang et al., 2013), multiple linear regression technique (Zhang et al., 2009), and sensitivity analysis (Gao, He, Dong, & Bian, 2016)). Nevertheless, due to complex interactions among various meteorological factors for ET0 (Paparrizos, Maris, & Matzarakis, 2016; Zhang et al., 2009; Zhang et al., 2013), it remains difficult to identify the impact of each driving factor alone, which consequently results in uncertainties and even errors in the conclusions (Li et al., 2016; Liu et al., 2016; Zhang et al., 2013).

Recently, to overcome this issue (at least partially) and enhance the confidence level of the conclusions, Sun, Chen, Ju, et al. (2017) developed a new separation method to attribute ET0 changes over Southwest China and stated that this method has a better performance (e.g., accuracy) compared with other methods. As a result, this provides an efficient tool to more accurately and comprehensively understand the underlying mechanisms of changed ET0 across China.

Furthermore, by considering the importance of ET0 for the estimation of crop water demand and drought forecasting systems (McEvoy et al., 2016), obtaining detailed information about ET0 is critical before developing countermeasures for policy makers. Large-scale atmospheric or coupled atmosphere–ocean modes of climate variability (usually referred to as teleconnections due to their long-distance range of influence) can provide a useful framework for linking ET0 to climate fluctuations via influencing climate variables (e.g., wind speed, solar radiation, temperature, and relative humidity; Chen, Li, & Pryor, 2013; Li & Chen, 2014; Yu, Zhong, Bian, & Heilman, 2015; Zhu et al., 2017). Given more knowledge of atmospheric system processes and the improved capability of future teleconnection predictions (Alexander, Matrosova, Penland, Scott, & Chang, 2008; Derome, Lin, & Brunet, 2005; Yang et al., 2015; Zheng, Fang, Zhu, Yu, & Li, 2016), estimating future ET0 has become more possible using historical and predicted teleconnection patterns. However, few studies (Meza, 2005; Sabzipurvar, Mirmasoudi, Tabari, Nazemosadat, & Maryanaji, 2011; Tabari, Talaeе, Some’e, & Willems, 2014) on the relationships between teleconnection patterns (represented by the Atlantic Oscillation [AO], North AO, Indian Ocean Dipole [IOD], Pacific Decadal Oscillation [PDO], and El Niño Southern Oscillation [ENSO] indices) and ET0 have been available so far, especially in China. For example, Tabari et al. (2014) found that winter ET0 over Iran was negatively correlated with the North AO index at almost all of the chosen stations. In summary, comprehensive analyses of the linkages between ET0 and teleconnection patterns can provide important information for ET0 prediction.

In short, in-depth discussions about the causes of ET0 changes on multiple timescales (e.g., seasonal and annual), and the linkages between ET0 and teleconnection patterns can provide important informational support for accurately estimating and predicting agricultural water requirements and reasonably making irrigation decisions, as well as facilitating a deep understanding of regional dry/wet (drought) conditions (Meza, 2005; Saadi et al., 2015; Shi et al., 2014). Therefore, the main objectives of this study are as follows: (a) to analyse seasonal and annual ET0 changes across China from 1960 to 2012, (b) to quantify the respective impact of each meteorological factor on ET0 changes and identify the dominant factors, and (c) to explore the relationships between teleconnection patterns and ET0.

2 | DATA AND METHODOLOGY

2.1 | Data

To compute ET0, monthly maximum and minimum temperature (°C), relative humidity (%), sunshine duration (hr), and wind speed at a
10-metre height (m/s) are measured from 1960 to 2012 at 1672 weather sites, which are collected from the China Meteorological Administration. These sites and the 10 basins across China are shown in Figure 1. Before using, two data quality issues within this dataset (i.e., inhomogeneous and missing values) should be noted; therefore, we have followed the methods of Sun, Chen, Ju, et al. (2017) to solve them. For simplicity, the detailed procedure is not presented here but can be found in Sun, Chen, Ju, et al. (2017). Considering that a nonuniform density distribution of the sites has potential impacts on the results, we follow J. Zhang et al. (2016) and process 1,209 sites into 548 grid boxes of 1° × 1° (longitude by latitude). Each grid box should contain at least one site with continuous meteorological measurements. If any grid includes more than one site, the average value of each meteorological variable at these sites is calculated to represent the final value of that grid. Notably, spring, summer, autumn, and winter are specified as March–May, June–August, September–November, and December–February, respectively.

China is located in a typical monsoon region (i.e., the East Asian monsoon region), which is significantly influenced by ENSO (Ding et al., 2014; He & Wang, 2013). The PDO can also regulate China’s climate (Feng, Wang, & Chen, 2014; Wang, Chen, & Huang, 2008). In addition, the East Asian monsoon has been influenced by the IOD and AO (Chen, Feng, & Wu, 2013; Ding, Ha, & Li, 2010; He, Gao, Li, Wang, & He, 2017; Yuan, Yang, Zhou, & Li, 2008). Therefore, monthly IOD, AO, ENSO, and PDO values from 1959 to 2012 are selected to investigate the relationships between teleconnection patterns and ET₀ in China. Definitions and sources of these four teleconnection indices are shown in Table 1.

2.2 Methodology

2.2.1 ET₀ estimation

We compute ET₀ using a modified Penman–Monteith equation (Allen, Pereira, Raes, & Smith, 1998), which has been recommended as a standard tool for climatic data by the Food and Agriculture Organization of the United Nations and can be written as follows:

\[
ET₀ = \frac{0.408 \Delta (RN - G) + \gamma \frac{900}{TAVE + 273} WND \cdot VPD}{\Delta + \gamma (1 + 0.34 \cdot WND)},
\]

where RN (MJ/(m² d)) is the difference between net incoming short-wave and net outgoing longwave radiation; G (MJ/(m² d)) denotes the soil heat flux, which can be ignored at monthly or longer timescales; \(\gamma\) (kPa/°C) and \(\Delta\) (kPa/°C) represent the psychrometric constant and slope vapour pressure curve, respectively; TAVE (°C) represents the mean temperature and can be estimated as the mean of the minimum and maximum temperature; WND (m/s) is the wind speed at a 2-metre height, which is converted from the wind speed at a 10-metre height; and VPD (kPa) denotes the vapour pressure deficit, which can be expressed as the difference between saturation and actual vapour pressure. All of the computations are performed on a monthly scale. Detailed equations for \(\Delta\), RN (which can also be found in Supporting Information), \(\gamma\), TAVE, WND, and VPD can be found in Allen et al. (1998).

2.2.2 Method for attributing ET₀ changes

To quantify each the individual contribution of each factor to the ET₀ trend, five experiments are designed, namely, one control experiment (Sim_CTR) and four sensitivity experiments for each driving factor (Sim_x, where x is RN, TAVE, WND, and VPD). All of these experiments are run from 1960 to 2012 but with different inputs. In detail, the Sim_CTR experiment is conducted with the original data, whereas the Sim_x experiments are run with the detrended monthly time series of the x-factor and the original data of the other three factors. For the detrending method, we followed J. Zhang et al. (2016), which can also be found in Supporting Information. For more clarity, the Sim_TAVE sensitivity experiment for temperature is shown as an example, which

![FIGURE 1 Location of 1,209 weather sites, 548 grid boxes, and 10 basins across China](image-url)
includes the inputs of the detrended monthly TAVE and the original monthly RN, WND, and VPD data.

Then, to distinguish the contribution from each factor alone, we can utilize the following equation:

\[ A_{C_i} = T_{Sim,CTR} - T_{Sim,i} \]

where \( A_{C_i} \) represents the contribution of the i-factor to ET0 change, and \( T_{Sim,CTR} \) and \( T_{Sim,i} \) denote the ET0 trend for Sim_CTR and Sim_i, respectively. Here, this method is named as approach A.

Due to the interactions among these driving factors, there exists the potential to introduce some uncertainties into the attribution of ET0 change. To eliminate the complex effects, Sun et al. (2014) and Sun, Chen, Ju, et al. (2017) proposed a new separation method (i.e., approach B), which is shown as follows:

\[ \sum_{k=i}^{n} B_{C_k} = T_{Sim,i} \]

where \( \sum_{k=i}^{n} B_{C_k} \) represents the accumulative contributions of all of the driving factors (except for the i-factor) to the ET0 trend; \( n \) is equal to 4 here and indicates the number of sensitivity experiments, and \( T_{Sim,i} \) represents the ET0 trend via Sim_i. As a result, the contribution of each factor alone can be obtained by solving Equation 3:

\[ B_{C_i} = \frac{\sum_{k=i}^{n} T_{Sim,i} - 2 \cdot T_{Sim,i}}{3} \]

For greater robustness and accuracy of the results, the performances of both approaches A and B are evaluated, which are shown in Table 2 and Figure S1. For the annual ET0 trend, the root mean square error (RMSE; mean relative error, MRE) is 0.057 mm/year (51.62%) and 0.019 mm/year (17.21%) for approaches A and B, respectively. As shown in Table 2, all seasonal RMSEs (<0.01 mm/year; MREs < 18%) via approach B are always smaller than those via approach A. In addition, Figure S1 displays the scatterplots of the cumulative contributions \( \sum_{k=1}^{4} \frac{1}{L} C_i \), where \( L \) is A or B) and the Sim_CTR ET0 trend at annual and seasonal scales. It is evident that relative to approach A, the results via approach B are closer to the 1:1 line (Figure S1). Therefore, approach B (with a higher accuracy and efficiency) is chosen to quantify the impacts of climate change on the ET0 trend in this study.

### 2.2.3 Relationships between ET0 and teleconnection indices

In this study, correlation coefficients are used to measure the strength of the relationships between ET0 and teleconnection patterns. On an annual scale, correlation analyses between ET0 and each teleconnection index (named y) are performed twice (the correlation coefficients of ET0 from 1960 to 2012 with the indices during the same period [named ARet0,y] and those from 1959 to 2011 [named ARet0,y,1]). It is noted that for each season, correlation analyses between ET0 and each teleconnection index are conducted four times, including the correlation coefficients between ET0 and indices with lead times of 0–3 season (s), which are named SRet0,y, SRet0,y,1, SRet0,y,2, and SRet0,y,3, respectively. Moreover, unless otherwise stated, the statistical significances of the linear trends and correlations in the following text correspond to a significance level of \( P < 0.05 \).

### 3 RESULTS

#### 3.1 Trend of ET0

Due to the coupling of various meteorological factors and large differences in the climate background, ET0 indicates obvious temporal (seasonal and annual) and spatial differences across China (Figures S2–S3). On an annual scale (Figure S3a), lower ET0 values (<1,000 mm) are found in the middle CJRB, south-western YRB, SHRB, and eastern LRB, but higher values (>1,200 mm) are found in NWRB, SWRB, and southern PRB. As depicted in the right panel of Figure 2, both seasonal and annual ET0 values for the whole China decrease, where annual and summer trends are significant and lower than –0.60 mm/year.

Except for the SWRB, which has a significant increase (0.69 mm/year; the left panel of Figure 2), the annual ET0 primarily shows decreases in other basins; moreover, the trends in the LRB, HRB, HaRB, and CJRB are significant, especially for the HaRB, with a maximum magnitude of 1.79 mm/year. Taking 4 seasons × 10 basins (40 cases), negative ET0 trends are detected in 29 cases, with nine cases that pass the given significance test. Because of the larger ET0 in summer, the largest changes always happen during this season for all basins (excluding

### TABLE 1 Definitions and sources of the selected teleconnection indices

| Indices | Definition | Sources |
|---------|------------|---------|
| IOD     | IOD, which usually referred to as Dipole Mode Index (DMI), is defined as difference between the SST anomalies of the western equatorial Indian Ocean and the southern equatorial Indian Ocean. | Japan Agency for Marine-Earth Science and Technology (JAMSTEC) |
| AO      | AO is referred as the first leading mode from the EOF (Empirical Orthogonal Function) analysis of monthly mean height anomalies at 1,000 hPa. | Earth System Research Laboratory (ESRL) of NOAA |
| PDO     | PDO is specified as the dominant year-round pattern of monthly North Pacific sea surface temperature (SST) variability. | ESRL |
| ENSO    | ENSO is indicated by the Niño-3.4 indices (average SST in the region bounded by 5°N–5°S and 120°W–170°W). | ESRL |

### TABLE 2 Statistics of approaches A and B performances at seasonal and annual scales

| Approaches | MRE (%) | RMSE (mm/year) |
|------------|---------|----------------|
| A          | Spring  | 17.37 | 0.018 |
|            | Summer  | 18.97 | 0.023 |
|            | Autumn  | 13.52 | 0.016 |
|            | Winter  | 31.25 | 0.005 |
|            | Annual  | 51.62 | 0.007 |

|          | Spring  | 5.79  | 0.005 |
|          | Summer  | 6.32  | 0.008 |
|          | Autumn  | 4.51  | 0.005 |
|          | Winter  | 10.42 | 0.001 |
|          | Annual  | 17.21 | 0.019 |
the SHRB and LRB in spring). In addition, it is worth noting that over the SHRB and SWRB, ET0 increases from summer to winter, particularly for ET0 during summer and autumn over the SWRB, which has larger (approximately 0.3 mm/year) and more significant trends.

As shown in Figure 3a and Table 3, most of the grids (66.3%) have decreased annual ET0; moreover, 34.2% of grids with significant decreases are mainly located in the HaRB, NWRB, HRB, and southern LRB and are accompanied by the largest decreases (<−2.5 mm/year) in the western HaRB and part of the NWRB. For grids in the SWRB, midwestern YRB, western SHRB, and mouth of the CJRB, annual ET0 trends are basically positive but insignificant. In spring (Figure 3b and Table 3), grids with increased (decreased) ET0 account for...
approximately 50% of the total, with significant changes generally in the mideastern CJRB and northern SERB (eastern SHR, LRB, and HRB, and north-western HaRB). During summer (Figure 3c and Table 3), \( ET_0 \) decreases for an overwhelming majority (70.7%) of grids, followed by 38.8% of grids with \( P < 0.05 \) in the eastern HRB and YRB, HaRB, mideastern CJRB, and NWRB. Autumn \( ET_0 \) (Figure 3d and Table 3) decreases in 53.5% of grids, which generally occurs in the NWRB, southern LRB, HRB, northern HaRB and eastern CJRB. Despite that 14.9% and 13.3% of grids have significant decreases and increases, respectively, these grids are relatively dispersed across China. In general, the spatial distribution of the \( ET_0 \) trend in winter (Figure 3e) is consistent with that in summer (Figure 3c), which is characterized by a decrease in most of the grids (61.6% in Table 3) over China (excluding the SHR and southern SWRB). Moreover, 17.7% of grids have significant decreases in winter \( ET_0 \) and are mainly concentrated at the juncture of the YRB, HaRB, and CJRB.

### 3.2 Changes in major meteorological factors

Changes in \( ET_0 \) are jointly affected by various meteorological factors, such as TAVE, VPD, WND, and RN; thus, it is necessary to know their variations to understand \( ET_0 \) changes. Figure 4 presents the seasonal and annual trends of these four factors in China and its 10 major basins. For the China regional average (the right panel of Figure 4), TAVE (WND) and VPD (RN) significantly change by 0.026°C/year (−0.011 m/[s year]) and 0.0017 kPa/year (−2.35 MJ/[m² year²]), respectively. In each basin (the left panel of Figure 4), the regional average annual TAVE and VPD show significant upward trends, but WND and RN have significant decreasing trends (except for SWRB). On a seasonal scale, TAVE significantly increases for the whole China and all basins (except for the HaRB in summer and PRB in spring); specifically, winter has the greatest warming (>0.02°C/year; Figure 4a).

![Figure 4](image-url)
Over China and each basin (Figure 4b), the regional average seasonal VPD increases at different rates, and most cases (32 of 4 seasons × 11 regions) pass the statistical significance test for \( P < 0.05 \). WND for each season significantly decreases in all study regions, particularly in the HaRB, with a maximum in spring (−0.025 m/[s year]; Figure 4c). Except for the SWRB and NWRB, which have slight increases in summer–winter and spring, respectively, RN significantly decreases for most of the remaining cases (Figure 4d). In addition, we calculate the annual and seasonal changes in these driving factors, which are illustrated in Figures S4–S7. Overall, the annual and seasonal TAVE and VPD (RN and WND) increase (decrease) for most (>70%) of the grids (Table S1), whereas the changing rates have obvious spatial differences.

### 3.3 Causes of \( \text{ET}_0 \) change

Using the separation method proposed by Sun et al. (2014) and Sun, Chen, Ju, et al. (2017), we have separated the individual contributions of TAVE, VPD, WND, and RN to attribute \( \text{ET}_0 \) trends. Figure 5 depicts the contribution of each factor alone to the regional mean \( \text{ET}_0 \) changes. For the whole China (the right panel of Figure 5a), increases in annual TAVE and VPD favour the ET process, which results in a positive contribution; however, annual WND and RN decrease, which hinders this process and leads to a negative contribution. The contributions of annual VPD, WND, RN, and TAVE alone are 0.97, −1.10, −0.62, and 0.15 mm/year, respectively; therefore, the major cause of decreased annual \( \text{ET}_0 \) for the whole China can be attributed to the decrease in WND. For each basin (the left panel of Figure 5a), both the regional average TAVE (WND) and VPD (RN) positively (negatively) contribute to annual \( \text{ET}_0 \). However, due to the regional differences in the magnitudes of each factor change, their contributions to annual \( \text{ET}_0 \) variations differ among basins, which consequently leads to different dominating factors (i.e., the major contributors are decreased WND in the SHRB, LRB, HRB, YRB, HaRB, and NWRB; decreased RN in the CJRB, SERB, and PRB; and increased VPD in the SWRB). On a seasonal scale (the right panel of Figure 5b–e), decreased RN and WND should be responsible for the regional mean \( \text{ET}_0 \) decreases in summer and the other three seasons in China, respectively. As depicted in the left panel of Figure 5b, except for the PRB, which has a dominant decrease in RN in spring, \( \text{ET}_0 \) changes are due to decreased WND or VPD values for the other nine basins. In summer (the left panel of Figure 5c), seven basins are characterized by RN as the major contributor, but changes to \( \text{ET}_0 \) in the SHRB and SWRB and NWRB are mainly caused by decreases in VPD and WND, respectively. During autumn (the left panel of Figure 5d), except for RN, which is dominant in the SERB, WND or VPD is the major contributor in the remaining basins. In winter (the left panel of Figure 5e), the SHRB and SWRB and PRB have dominant decreases in VPD and RN, respectively, whereas decreased WND determines \( \text{ET}_0 \) changes in the other seven basins.

![FIGURE 5](image-url) Contributions of each driving factor alone to seasonal and annual \( \text{ET}_0 \) changes over each basin and the whole China. Asterisk denotes dominant factor.
Figure 6 shows the spatial distributions of the individual contributions from each factor to the annual ET₀ trend. For an overwhelming majority of the grids (Figure 6a), the contribution of annual TAVE is positive but smaller (<0.4 mm/year). Notably, the TAVE contribution is negative in some grids over the NWRB, even though TAVE actually rises. This may be because of the limited impacts of TAVE on ET₀ and the uncertainties of the utilized separation method. In response to the general increase in VPD over China, ET₀ tends to increase at different rates (Figure 6b). In some grids over the NWRB, YRB, and south-eastern coastal areas, the VPD contribution to annual ET₀ change is greater than 1.5 mm/year. In contrast, an overwhelming majority of grids experience a negative WND contribution (Figure 6c) over China; moreover, the WND contribution is basically lower than −1.5 mm/year north of the CJRB, which corresponds to areas with larger WND decreases (Figure S6a). Given the decreased RN in Eastern China (Figure S7a), the RN contribution to ET₀ change is negative and larger (<−1.0 mm/year) in the HRB, eastern YRB, north-eastern CJRB and northern SERB (Figure 6d) but generally positive and smaller (<0.4 mm/year) in Western China in response to the slight increases in RN.

Based on the seasonal and annual contributions of each driving factor alone to ET₀ trends (Figure S8), we identify the dominant factors affecting ET₀ changes (Figure 7) in all grids and calculate their percentages in the grids (Table 4). On an annual scale (Figure 7a and Table 4), the WND is a dominant factor that corresponds to the largest percentage (43.1%) over China and is mainly located north of the CJRB (excluding the midwestern YRB and western SHRB). The VPD is found to be a dominant factor in 30.8% of grids, but it is dispersely distributed and mainly exists in the south-eastern SWRB, midwestern YRB, and south-eastern coast; 24.8% of grids that are dominated by RN mainly appear over the mideastern CJRB and most of the PRB and SERB. Because of the smaller contribution from TAVE across China, only 1.3% of grids are dominated by TAVE. Seen from Table 4, WND is the dominant factor that covers the largest spatial extent in spring (45.2%), autumn (43.2%), and winter (53%), whereas RN is the dominant factor that accounts for a maximum percentage (53%) in summer. Specifically, TAVE, as a dominant factor, always corresponds to a smaller percentage (<3%) for each season. For the spatial patterns of dominant factors in each season (Figure 7b–e), evident seasonal differences are detected. In detail, WND, as a major contributor, in spring is mainly concentrated over the SHRB, LRB, HRB, NWRB, and northern HaRB (Figure 7b). Moreover, the dominant factor of VPD in spring is also worth noting (accounting for 43.1% of the grids), which mainly influences the mideastern CJRB, YRB, and south-eastern coast (Figure 7b). In summer (Figure 7c), RN is dominant for a much larger area (53%) than any other dominant factor and is concentrated in basins in Eastern China (excluding the SHRB). During autumn, 43.2% of grids that are dominated by WND generally exist over the NWRB, LRB, HRB, and HaRB (Figure 6d) but generally positive and smaller (<0.4 mm/year) in Western China in response to the slight increases in RN.

Based on the seasonal and annual contributions of each driving factor alone to ET₀ trends (Figure S8), we identify the dominant factors affecting ET₀ changes (Figure 7) in all grids and calculate their percentages in the grids (Table 4). On an annual scale (Figure 7a and Table 4), the WND is a dominant factor that corresponds to the largest percentage (43.1%) over China and is mainly located north of the CJRB (excluding the midwestern YRB and western SHRB). The VPD is found to be a dominant factor in 30.8% of grids, but it is dispersely distributed and mainly exists in the south-eastern SWRB, midwestern YRB, and south-eastern coast; 24.8% of grids that are dominated by RN mainly appear over the mideastern CJRB and most of the

**FIGURE 6** Spatial distributions of respective contributions from each driving factor to annual ET₀ changes.
3.4 Relationships between ET₀ and various teleconnection indices

Annual correlation coefficients between ET₀ and the four selected teleconnection indices are first calculated for the whole China and all of the basins, which are presented in Table 5. Among these annual correlation coefficients, both ARₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑₑ锷
correlations in the HaRB and middle CJRB (NWRB, HRB, CJRB, and PRB). Specially, the grids can be significantly influenced by a 1-year lead time for ENSO; this occurs in the north-eastern NWRB, HRB, and middle SHRB.

To provide more detailed information for predicting seasonal ET0 at different spatial scales (i.e., the whole China, basin, and grid scales), we compare SRet0,y, SRet0,y_1, SRet0,y_2, and SRet0,y_3 and identify their maximums (referred to as MSR), which are illustrated in Figure 9. For the whole China, there is at least one significant MSR for seasonal ET0 (i.e., SRet0,PDO_2 and SRet0,ENSO_1 in spring; SRet0,AO_3, SRet0,PDO_1, and SRet0,ENSO in summer; SRet0,ENSO in autumn, and SRet0,AO_3 in winter). During these seasons (except for autumn), a significant MSR appears at least once for each basin, excluding the LRB in spring, HaRB and SERB in summer, and NWRB in winter. By contrast, the MSRs in autumn are found to be insignificant over the four basins, which suggest that these indices are limited indicators for predicting autumn ET0 over these regions; particularly, the MSRs for autumn ET0 are all significant in the YRB, implying that all indices have the potential to be predictors for autumn ET0 in this basin. Additionally, it is not difficult to find that winter ET0 is always significantly correlated to AO among all basins (excluding the LRB and NWRB), even though the AO corresponds to different lead seasons. This indicates that the AO has the universality to be a predictor for forecasting the basin-average winter ET0 across China. Figure 10 shows the spatial patterns of the lead season (s) for each index, which shows the MSR with seasonal ET0. In spring (Figure 10(a1) and Table S3), grids with significant MSRs account for more than 22% for the four indices, which are generally distributed over the north-western NWRB and south-western YRB and SERB for the IOD; northern SHRB, southern SWRB, and south-east coastal areas for the AO; NWRB, YRB, HRB, HaRB, eastern PRB, and SERB for the PDO; and NWRB, HRB, HaRB, and southern SWRB for ENSO. Furthermore, as seen from the spatial extents of the significant MSRs, the PDO (48.9% of grids) is most significant for predicting spring ET0, and ENSO is the second most significant (Table S3). It is evident that during summer (Figure 10(b1–b4) and Table S3), grids with significant MSRs are mainly located in the western YRB, SHRB, and LRB for the IOD and NWRB, YRB and most of the CJRB for the PDO, which corresponds to percentages of 28.4% and 41.9%, respectively, whereas grids with significant MSRs for the AO and ENSO are relatively scattered across China. As shown in Table S3, the grid percentages with significant autumn MSRs range from 26.8% for the IOD to 42.9% for ENSO; moreover, these grids for the IOD (ENSO) mainly appear at the juncture of the YRB, HaRB and CJRB, western PRB, and south-eastern CJRB (YRB, southern HRB,

### TABLE 5  Annual correlation coefficients between ET0 and four teleconnection indices in each basin and China

| Correlation coefficients | SHRB | LRB | HRB | YRB | HaRB | CJRB | SERB | PRB | SWRB | NWRB | China |
|--------------------------|------|-----|-----|-----|------|------|------|-----|------|------|-------|
| ARet0,IOD                | 0.25 | 0.21 | 0.11 | 0.31 | 0.01 | 0.08 | 0.14 | -0.04 | 0.09 | 0.18 | 0.22  |
| ARet0,IOD_1              | -0.10 | -0.18 | -0.23 | -0.09 | -0.15 | 0.07 | 0.09 | 0.19 | 0.16 | -0.13 | -0.08 |
| ARet0,AO                 | 0.23 | 0.03 | -0.30 | -0.42 | -0.29 | -0.24 | -0.14 | -0.19 | -0.22 | -0.25 | -0.31 |
| ARet0,AO_1               | -0.21 | -0.24 | -0.21 | -0.09 | -0.28 | -0.34 | -0.17 | -0.13 | -0.19 | -0.21 | -0.35 |
| ARet0,PDO                | -0.18 | -0.16 | -0.21 | -0.20 | -0.14 | -0.35 | -0.30 | -0.23 | 0.05 | -0.42 | -0.40 |
| ARet0,PDO_1              | -0.017 | -0.13 | -0.28 | -0.25 | -0.18 | -0.31 | -0.23 | -0.30 | 0.05 | -0.38 | -0.38 |
| ARet0,ENSO               | 0.02 | 0.09 | 0.05 | 0.23 | 0.01 | -0.11 | -0.06 | 0.003 | 0.15 | -0.11 | 0.004 |
| ARet0,ENSO_1             | -0.26 | -0.24 | -0.33 | -0.20 | -0.07 | -0.03 | 0.01 | 0.02 | 0.13 | -0.43 | -0.28 |

Note. Bold number denotes that the correlation coefficient is significant with $P < 0.05$.

**FIGURE 8**  Spatial distributions of annual correlation coefficients between ET0 and four teleconnection indices. Asterisk denotes that the correlation coefficient is significant with $P < 0.05$.
### FIGURE 9
Maximums of seasonal correlation coefficients between ET₀ and a certain index with a lead time of 0–3 seasons for each basin and China. Bold number suggests that the correlation coefficient is significant with \( P < 0.05 \).

### FIGURE 10
Spatial distributions of lead season (s) of each index, which corresponds to the MSR. Asterisk denotes that this MSR is significant with \( P < 0.05 \).
HaRB, north-central CJRB, and middle PRB), but for the AO and PDO, these grids appear in regions north of the CJRB (Figure 10(c1–c4)). Regarding significant winter MSRs (Figure 10(d1–d4) and Table S3), grids influenced by the IOD, PDO, and ENSO are limited (<18% of grids) and basically occur in northern SHRB, eastern LRB, and the mouth of the CJRB, SHRB, NWRB, and southern SWRB, and SERB, eastern PRB, and southern SWRB, respectively. However, 49% of grids with significant MSRs are influenced by the AO and widely distributed across China, including the northern SHRB, YRB, PRB, SERB, southern SWRB, and middle CJRB. In addition, based on comparisons of the spatial distributions and grid percentages of significant MSRs (Figure 10 and Table S3), we can conclude that the PDO is more significant for predicting spring and summer ET\(_0\) for approximately half of the grids, but ENSO and the AO influence autumn and winter ET\(_0\) estimates, respectively.

4 | DISCUSSIONS

4.1 | Comparison of results

In the present study, a decrease in WND (RN) is concluded to be a major determinant factor for annual ET\(_0\) changes for the whole China and 43.1% (24.8%) of grids, which are mainly located over the HRB, northern HaRB, eastern YRB, southern LRB, and most of the NWRB (mideastern CJRB and most of the PRB and SWRB). The results are generally consistent with existing findings (e.g., Han, Xu, & Wang, 2012; Yin et al., 2010; Zheng & Wang, 2015). For example, Yin et al. (2010) suggested that WND plays a dominant role in ET\(_0\) change in Western and Northern China, but RN is dominant in Southern China. Zhang et al. (2013) showed that ET\(_0\) is dominated by RN in humid regions and WND in the arid and semiarid regions of China. In addition, the result that WND is a dominant factor for decreased annual ET\(_0\) in the HRB is consistent with the results from Tang et al. (2011). Huo, Dai, Feng, Kang, and Huang (2013) and Li et al. (2016) explored the cause of ET\(_0\) changes in Northwest China and the Loess Plateau, respectively, and their conclusions generally agree with our results.

4.2 | Causes for trends in meteorological factors

Similar to those in other parts of the globe (Roderick & Farquhar, 2002; Stanhill & Cohen, 2001; Vautard, Cattiaux, Yiou, Thépaut, & Ciais, 2010), both seasonal and annual WND and RN are found to decrease from 1960 to 2012 for the whole China and most of the 548 grids; furthermore, the findings generally coincide with the previous results in China and its subregions (e.g., Lin, Yang, Qin, & Fu, 2013; Wang, Yang, Han, Wang, & Zhang, 2013; Xu et al., 2006; Yang, Zhao, Hu, & Zhou, 2009). To explain the decreased WND, many scholars have conducted various studies from the perspective of large-scale atmospheric circulation (e.g., Jiang, Luo, Zhao, & Tao, 2010; Xu et al., 2006). For example, Jiang et al. (2010) and Xu et al. (2006) pointed out that decreases in temperature vary between the Asian continent and the low-latitude region of the ocean, which are responsible for decreased WND over China. In addition, human activities, such as land use/cover change (e.g., urbanization) and air pollution, can also exert impacts on WND (Ren et al., 2008; Wang, Feng, & Gao, 2014; Xu et al., 2006). Regarding the possible causes of RN reductions, previous studies have suggested that cloud coverage and air pollution and aerosol loading from rapid urbanization are potential reasons (Qian, Kaiser, Leung, & Xu, 2006; Xia, Wang, Chen, & Liang, 2006; Yang et al., 2009). Zhu et al. (2017) found that large-scale atmospheric or coupled atmosphere–ocean modes are strongly associated with cloud cover across the world, which leads to RN variations. Moreover, with a weaken WND in China, air pollution and aerosol loading cannot be rapidly dispersed, which results in the further decrease in RN (Yang et al., 2009).

Under the background of global warming possibly caused by anthropogenic activities (e.g., greenhouse gases emissions; IPCC, 2014; Xu, Gao, Shi, & Zhou, 2015), annual and seasonal TAVE basically respond to significant increases at national and grid scales in our study. Notably, there are evident differences in warming rates across China, which are closely associated with the regional characteristics of the land surface’s energy balance (Dong, Xi, & Minnis, 2006; Stanhill & Ahiman, 2014; Wild, Grieser, & Schär, 2008; Wild, Ohmura, & Makowski, 2007), especially for the longwave radiation budget. Notably, temperature fluctuations are also linked to climate variability signals (Chen, Chen, Bai, & Xu, 2016; Guo, Zhao, & Dong, 2015). For example, Guo et al. (2015) noted that the AO plays an important role in variations in winter surface air temperature over China. Chen et al. (2016) found that the PDO can exert significant impacts on interdecadal temperature fluctuations over Northwest China, whereas the IOD plays a more important role in annual warming. For an overwhelming majority of grids, there are consistent increases in annual and seasonal VPD, which is consistent with the conclusions from Yang and Yang (2012). It is well known that the VPD is jointly controlled by TAVE and relative humidity (RH); furthermore, the VPD experiences increases (decreases) with increased TAVE (RH) when RH (TAVE) is constant and vice versa. To address this issue, we have analysed RH changes across China and found that annual and seasonal RH generally decreases across China (not shown here), which is possibly due to less moisture from oceans (Li & Chen, 2014; Simmons, Willett, Jones, Thorne, & Dee, 2010). Thus, we conclude that increased VPD for most of China can be attributed to increased TAVE and decreased RH.

Additionally, based on the discussions above and previous studies (e.g., Chen et al., 2016; Guo et al., 2015), we can basically obtain the underlying mechanisms of teleconnection impacts on ET\(_0\) by causing variations in climate variables (e.g., TAVE, RN, relative RH, and WND). This is why teleconnection indices are significantly correlated with ET\(_0\) at different timescales in some regions (Figures 8–10).

4.3 | Uncertainties

This study presents a relatively comprehensive investigation regarding climate change impacts on ET\(_0\). However, we should note that some factors (e.g., CO\(_2\) concentration, land-surface albedo, and resistance) related to the ET process are not considered; thus, uncertainties are potentially introduced into our results. Increased CO\(_2\) concentrations can not only lead to atmospheric warming but also smaller plant stomata and lower stomatal conductance (Gopalakrishnan et al., 2011), which finally reduce plant ET (Islam, Ahuja, Garcia, Ma, & Saseendran, 2012; Kergoat et al., 2002; Lockwood, 1999). However, other studies
have proposed different viewpoints. For example, Reid et al. (2003) found that due to the impacts of influential elements (e.g., water supply) associated with the physiological functions of plants, the stomatal characteristics of plants do not change with increasing CO₂, Li, Kang, and Zhang (2004) and Peng, Dan, and Dong (2014) reported that increases in CO₂ are conducive to plant growth and leaf area increases, which consequently intensify ET. In a word, elevated CO₂ impacts on ET are still questionable to date. Land-surface albedo (set as a constant of 0.23 here) change is also a source for uncertainties in this study. This parameter determines the ability of land surfaces to absorb solar radiation, which can affect the ET process by altering land-surface radiative forcing (Twine, Kucharik, & Foley, 2009). As we know, albedo differs among various types of land use/cover (Barnes & Roy, 2008); therefore, land use/land cover changes likely change albedo (Lee et al., 2011; Wu, Zha, & Zhao, 2015). In recent years, due to rapid social and economic developments in China, major adjustments and structural changes have occurred in the spatial patterns of land use/cover (Liu et al., 2010). It has been reported that recent land use/land cover changes in China have resulted in a general decrease in albedo (Wang et al., 2014; Zhai, Liu, Liu, Zhao, & Huang, 2014) but with obvious regional differences. Taking the Beijing–Tianjin–Tangshan area as an example, the conversion of agricultural land to urban areas decreases albedo, which results in more energy for ET (Zhai et al., 2014). However, less energy in the Sanjiang Plain is partitioned for ET due to increased albedo, which is mainly associated with the replacement of forests by farmlands (Zhang, Wang, Fang, Ye, & Zheng, 2012). Land-surface resistance can control the ET process by influencing the flow resistance of water vapour during crop transpiration and surface evaporation (Allen et al., 1998; Boegh, Soegaard, & Thomsen, 2002). Shuttleworth and Gurney (1990) pointed out that land-surface resistance is associated with the plant type, climate conditions, canopy structure and plant–soil water status, implying that land-surface resistance varies with space and time. However, the impacts of these factors on resistance are not included in the Penman–Monteith model, as this parameter is set to 70 s/m based on Twine, Kucharik, & Foley (2009). As a result, a fixed land-surface resistance tends to produce uncertainties. In spite of the used separation method with a better performance (i.e., lower MRE and RMSE), biases between the cumulative contributions from all driving factors and the Sim_CTR trends still exist (Figure S1); therefore, we should keep in mind the uncertainties from the limitations of this method. First, the key concept of this separation method is that ET₀ changes are linearly and jointly induced by all factors; however, each factor’s impacts are indeed complex and nonlinear, which can be found via the Penman–Monteith equation (Equation 2). Moreover, impacts from the interactions among these driving factors are not completely separated. For Sim_x, the corresponding ET₀ variations are caused by the other three factors and their interactions, but the Sim_x ET₀ trends are hypothesized to be equal to the linear cumulative contributions of the other three factors (by not considering the interactions).

To explore the linkage between ET₀ and teleconnection patterns, we have calculated linear correlation coefficients between ET₀ and four indices with different lead times. It is beyond a doubt that the analyses provide preliminary and necessary information (i.e., which index has a significant correlation with ET₀ and where) for predicting ET₀. Nevertheless, it is a fact that the relationships between ET₀ and teleconnection patterns are complex and nonlinear; therefore, using linear correlation analyses is not sufficient for understanding the linkage between ET₀ and these indices. In past decades, general atmospheric circulation models or earth system models have made great progress and provided ideal and efficient tools to comprehensively study the underlying mechanisms of various hydrometeorological issues. However, it should be noted that our major aims are to attribute ET₀ changes and quickly identify potential predictors for estimating ET₀, and there are still some difficulties when diagnosing the linkages between ET₀ and teleconnection patterns with models (i.e., how to reasonably design numerical experiments due to the higher complexity of the atmosphere system). Therefore, applying models for investigating the relationships between ET₀ and these indices may be beyond the scope of this study (at least now). Regardless, we would like to conduct in-depth studies about this issue using models in the future, which will enhance the confidence level of our conclusions.

5 | CONCLUSIONS

Comprehensive analyses of the spatio-temporal changes in ET₀ from 1960 to 2012, which are estimated based on the Penman–Monteith equation and routine meteorological measurements, are conducted in this study. Overall, the annual and seasonal ET₀ values averaged over China and each basin generally show downward trends but with different magnitudes. To understand ET₀ changes and the underlying mechanisms, we analyse variations in four driving factors (i.e., TAVE, VPD, WND, and RN) of ET₀ and calculate the corresponding contribution of each factor alone to ET₀ trends via several numerical experiments and a separation method (Sun et al., 2014; Sun, Chen, Ju, et al., 2017). Regarding these factors, there are significant annual and seasonal changes for the whole China, most of the basins and an overwhelming majority of grids (i.e., VPD and TAVE increase, but WND and RN decrease). Comparisons of the contributions of each factor alone suggest that dominant factors affecting ET₀ changes vary at spatial (i.e., the whole China, basin, and grid) and temporal (i.e., annual and seasonal) scales. Except for the whole China, which is dominated by RN in summer, WND is the largest contributor for annual and seasonal ET₀ changes. For the basins north of the CJRB, annual ET₀ changes can be attributed to decreased WND, accounting for approximately 43.1% of grids, whereas the other basins are dominated by RN or VPD. For each season, the WND reduction is the major cause for changed ET₀ in most of the grids north of the CJRB, but there are still some grids (generally in the YRB during spring and autumn and SHRB during autumn and winter) that are dominated by VPD; however, the dominant factors in and south of the CJRB evidently differ among seasons, which is mainly characterized by a complex spatial distribution. In summer, with the exception of dominant factors WND and VPD in the NWRB, SWRB, SHRB, and western YRB, decreased RN should be responsible for ET₀ variations. More importantly, despite consistent and significant warming across China, TAVE has many limited impacts on seasonal and annual ET₀ variations.
To sum up, this detailed information about the attributions of ET₀ changes will be useful to further understand dry/wet conditions (e.g., ongoing and intensifying droughts over some parts of China) and guide policy makers for the management of water resources and agricultural production activities.

Lastly, annual and seasonal correlations between ET₀ and the four teleconnection indices (i.e., IOD, AO, PDO, and ENSO) with different lead times are estimated. In general, there are always significant correlations between ET₀ and each index in some regions, but the locations and spatial extents vary considerably among different indices at given lead times. Overall, the AO and PDO have the potential to be predictors for forecasting annual ET₀ at different spatial scales (i.e., the whole China, basin, and grid scales). For each season, the PDO has greater significance for predicting spring and summer ET₀, but ENSO and AO are more significant for predicting autumn and winter ET₀, respectively. Undoubtedly, these correlation analyses will provide fundamental and important reference information for predicting ET₀ with the statistical forecast method, which has a potential application in climate forecasting systems.

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ORCID
Shanlei Sun http://orcid.org/0000-0002-7237-2722
Haishan Chen http://orcid.org/0000-0002-2403-3187

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