1. Introduction

The Tibetan Plateau (TP) has become a climate change hot spot due to its crucial role in Earth’s climate system as well as its sensitivity to global warming (Li et al. 2020, Duan and Xiao, 2015, Zhang et al. 2013). TP has undergone more rapid warming (0.5 °C decade^{-1}), which is about twice the global average, than other places over the world (Yao, 2019). Rising temperatures (Zheng et al. 2020, Zhang et al. 2021b) accompanied by the increased precipitation variability (Chen et al. 2013, Du et al. 2015, Li et al. 2018) would have a marked influence on vegetation dynamics. Therefore, understanding the spatiotemporal changes of vegetation dynamics on the TP and the impact of climate change on it are crucial for assessing the impacts of anticipating future changes and developing adaptive ecosystem management measures (Li et al. 2020).

It is believed that the long-term variations of plant growth are mainly influenced by climatic drivers on the TP, including temperature, precipitation, radiations, wind speed, and others (Camberlin et al. 2007, Detsch et al. 2007). This study focuses on the relationship between climatic drivers and vegetation growth across the TP by using the normalized difference vegetation index (NDVI). The NDVI is a widely used remote sensing index to monitor vegetation health and productivity on a global scale (Huete, 1988).

Our results show that NDVI is used as a proxy for vegetation growth and productivity, which is positively correlated with temperature and precipitation, and negatively correlated with vapor pressure deficit (VPD). These findings contribute to a systematic understanding of the possible mechanisms underlying the responses of vegetation growth to various climatic drivers across the TP.
2016, Zhu 2016). The response of vegetation growth to temperature is relatively complex. A higher temperature could stimulate metabolism (Gao et al 2013, Shen et al 2016), extend the growing season (Piao et al 2011), and correspondingly promote vegetation productivity on the TP (Zhang et al 2014). Nevertheless, the contrary may also hold and has been supported by observations in the sense that higher temperatures enhance surface evapotranspiration and lead to further water stress affecting vegetation growth on the TP, especially in arid and semi-arid regions (Ganjurjav et al 2016, Huang et al 2016a, 2016b). Precipitation increase has been shown to strengthen vegetation growth in the northeastern and southwestern TP (Du et al 2015, Li et al 2018) but impede it in the southeast region (Hua and Wang, 2018). More recently, evidence from observations reveals a clear impact of warming (Zhang et al 2021b) and wetting (Peng et al 2021) on vegetation processes over the TP. Aside from temperature and precipitation, vegetation growth on the TP has also been found to be affected by solar radiation (Li et al 2016, Peng et al 2021), wind speed (You et al 2010), and vapor pressure deficit (VPD) (Ding et al 2018). Nonetheless, the main drivers of vegetation growth changes may exhibit regional behaviors (Jin et al 2021, Wang et al 2021, Zhu et al 2021).

As an effective index of vegetation growth, normalized difference vegetation index (NDVI) has been widely used to study the temporal and spatial changes of plant growth in the TP region (Pang et al 2017, Li et al 2020). NDVI is an effective tool to depict the spatiotemporal evolution characteristics of vegetation processes across multiple spatial and temporal dimensions as well as various vegetation types (Piao et al 2003, Xu et al 2022). Spatiotemporal changes of NDVI, as well as its response to climate change, have been widely documented over the past years (Zhou et al 2007, Piao et al 2011, Zhong et al 2019, Li et al 2020), which greatly advances our understanding of the change in vegetation dynamics across the plateau. For instance, Zhou et al (2007) reported that NDVI on the TP has significantly increased from 1982 to 2002, which is mainly controlled by temperature variations. Further, Piao et al (2011) found a positive correlation between vegetation dynamics and temperature across alpine ecosystems on the TP. More recently, Li et al (2020) demonstrated that precipitation controls NDVI dynamics dominantly across the northeastern and southwestern regions on the TP. However, a closer look at the previous studies reveals several gaps. For example, most of these studies are based on a relatively short period of NDVI dataset, while there are few studies on systematically investigating the impacts of climatic drivers on NDVI changes for different vegetation types during a long-term period over the whole TP. Given the response of vegetation greening to climatic drivers has strong spatial heterogeneity on the TP (Detsch et al 2016), it is crucial to explore the change in plant growth to its full complexity by considering the spatial variability of vegetation types, climatic conditions, and topography using the longest available dataset over the TP. A comprehensive attribution analysis that links spatiotemporal changes of vegetation growth on the TP with multiple climatic drives is required.

Here, based upon the daily satellite-measured NDVI data from 1982 to 2018, we determined the length of the growing season by the dynamic threshold method and extracted the corresponding NDVI value (NDVI$_{CGS}$) across the TP. Then, we used satellite-measured NDVI data and climatic data to investigate how the climatic drivers impact NDVI in the growing season over the TP during 1982–2018. We also examined how the relationship may vary across different plant types on the Tibetan Plateau. Our objectives in this study are three-fold: (1) to explore temporal changes of NDVI and climatic drivers during the growing season from 1982 to 2018; (2) to reveal the dependency of vegetation dynamics on vegetation types; and (3) to systematically identify the connection between climatic factors and vegetation dynamics, and the possible mechanisms underlying the observed spatiotemporal patterns across the TP.

2. Data and methods

2.1. Data

2.1.1. NDVI Datasets
NDVI data from 1982 to 2018 were retrieved based on the 16-day NDVI data of AVHRR and MODIS. For a detailed description of the NDVI data, a reference is made to Zhang et al (2015). We derived a daily NDVI series for each 8 km grid cell using temporal linear interpolation of adjacent semi-monthly values (Zhang et al 2010). The domain of this investigation covers the whole areas of the Tibetan Plateau excluding permanent ice, non-vegetated areas, and urban areas (figure 1). The boundary of the study area is defined and provided by China’s National Tibetan Plateau Data Center (http://data.tpdc.ac.cn). The spatial resolution of the NDVI records is 25 × 25 km$^2$. Before analysis, bilinear interpolation is used to resample all data to the same resolutions as that of NDVI.

2.1.2. Climate drivers datasets
The China Meteorological Forcing Dataset (CMFD) (https://data.tpdc.ac.cn/en/) was used to examine the long-term (1982–2018) changes in climatic drivers including average air temperature (T), precipitation (P),
downward longwave radiation ($L_{rad}$), downward shortwave radiation ($S_{rad}$), wind speed ($u_2$), specific humidity ($q$), and air pressure ($p$). The CMFD is based on the fusion of remote sensing products, reanalysis datasets, and observations from weather stations with a spatial resolution of 0.1° (Yang and He, 2019, He et al 2020). All the climatic datasets were extracted corresponding to the growing season.

### 2.2. Methods
#### 2.2.1. Determination of the growing season

Most studies tend to directly choose April-October (according to common phenology) or March-November (according to season division) as the growing season (GS). However, annual average temperature of the TP is significantly lower than that of other regions at the same latitude. A predefined period for vegetation’s growing season may not reflect the true condition of vegetation greening. Therefore, we identified the beginning and end of the growing season ($G_{start}$ and $G_{end}$) using the dynamic threshold method (Richardson et al 2010). More specifically, dynamic thresholds defined as $\text{NDVI}_{\text{ratio}}$ of 20% or 50% were used to determine $G_{start}$ and $G_{end}$ (Zhang et al 2018, Shen et al 2014, White et al 2009).

$$\text{NDVI}_{\text{ratio}} = \frac{\text{NDVI}_t - \text{NDVI}_{\text{min}}}{\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}}}$$  \hspace{1cm} (1)

where $\text{NDVI}_t$ represents the NDVI value at a given time $t$; and its maximum and minimum values are $\text{NDVI}_{\text{max}}$ and $\text{NDVI}_{\text{min}}$, respectively. To be more specific, the first day of the year on which the $\text{NDVI}_{\text{ratio}}$ is larger/less than 0.5 (TR5S) in the spring/autumn is determined as $G_{start}$/$G_{end}$; $G_{end}$ minus $G_{start}$ is the length of the growing season ($L_{GS}$). $\text{NDVI}_{GS}$ is defined as the average value of NDVI during the growing season for every year.

#### 2.2.2. Estimation of trends in $\text{NDVI}_{GS}$ and climatic drivers

To quantify the trends in $\text{NDVI}_{GS}$ and climatic variables, we employed the simple linear regression method with the Theil–Sen estimator (Sen, 1968) to estimate the slope of trends. As a non-parametric estimator, Sen’s slope estimator is insensitive to outliers and is effective for skewed and heteroskedastic data. All trends were determined by the Mann-Kendall test and tested at the significance level of 0.05 (Mann, 1945, Kendall, 1975).

#### 2.2.3. Attribution analysis methods

In this study, we used three methods including the standardized multivariate linear regression, partial least squares regression, and partial correlation analysis to explore the possible associations between plant growth and climatic variables.

Standardized multivariate linear regression is a regression analysis method for studying the relationships between multiple variables. The importance of each driver can be presented by the coefficient before each driver, which can be expressed as:

$$\frac{\text{NDVI}_{GS} - \bar{\text{NDVI}}_{GS}}{\sigma_{\text{NDVI}_{GS}}} = \beta_0 + \beta_1 \frac{\text{F}_1 - \bar{\text{F}}_1}{\sigma_1} + \ldots + \beta_n \frac{\text{F}_n - \bar{\text{F}}_n}{\sigma_n}$$  \hspace{1cm} (2)
where \(IF_i\) \((i = 1, 2, \ldots, n)\) are climatic drivers; \(\text{NDVI}_{iG}^S\) and \(\overline{\text{NDVI}_{iG}^S}\) are multi-year means of \(\text{NDVI}_{iG}^S\) and various drivers, respectively; \(\sigma_{\text{NDVI}_{iG}^S}\) and \(\sigma_i\) are standard deviations of \(\text{NDVI}_{iG}^S\) and climatic indicators, respectively; and \(\beta_1, \beta_2, \ldots, \beta_i\) \((i = 1, 2, 3, \ldots, n)\) are regression coefficients. The factor with a larger coefficient contributes more to the change of \(\text{NDVI}_{iG}^S\). We computed the variance inflation factor (VIF) to avoid multicollinearity for all indicators before applying the standardized multivariate linear regression method.

Partial least squares regression contains the basic functions of standardized multivariate linear regression, principal component analysis, and canonical correlation analysis, which overcome the multicollinearity problem between two or more explanatory variables effectively (Chun and Keles, 2010, Mehmood et al. 2012, Chun and Keles, 2019). Variable importance in projection (VIP) is the criterion to judge the importance of independent climatic drivers in the partial least squares regression. When VIP of one driver is greater than or equal to 1, indicating it can explain the dependent variable convincingly (Wold, 1995, Chong and Jun, 2005). Prior applying the partial least squares regression, all climatic drivers were also standardized.

Partial correlation analysis is usually applied to explore the correlation degree between two variables under the condition of controlling and eliminating the influence of other variables, which is widely applied to detect the relationship between the plant growth and a single climatic driver and remove the influence of other drivers (Wu et al. 2015, Shen et al. 2016). We used it to determine the correlation between climatic drivers and vegetation growth, which can be expressed as follows:

\[
\rho_{xy,z} = \frac{\rho_{xy} - \rho_{xz} \rho_{yz}}{\sqrt{(1 - \rho_{xz}^2)(1 - \rho_{yz}^2)}}
\]

where \(\rho_{xy,z}\) is the coefficient between the \(x\) and \(y\) under the control factor \(z\). The relationship between \(\text{NDVI}_{iG}^S\) and its related climatic variables for different plant types was analyzed through partial correlation analysis. The time series involved are detrended before analysis to eliminate the impact of trends (Yuan et al. 2019). A correlation is classified as a ‘significant positive/negative correlation’ when its p-value is less than 0.05, a ‘no correlation’ when its p-value is larger than 0.1, and a ‘positive/negative correlation’ otherwise.

### 3. Results

#### 3.1. Climatology and trends in \(\text{NDVI}_{iG}^S\)

\(\text{NDVI}_{iG}^S\) has a clear spatial gradient with increasing value from the northwest to the southeast (figure 2(a)). The regional average \(\text{NDVI}_{iG}^S\) across the TP is 0.32 ± 0.177 (figure 2(a)). From 1982 to 2018, approximately 86% of the TP vegetated surface shows a significant increasing trend \((p < 0.05)\) in \(\text{NDVI}_{iG}^S\) (figure 2(b)). More importantly, the spatial distribution of the \(\text{NDVI}_{iG}^S\) trend is very similar to the spatial pattern of \(\text{NDVI}_{iG}^S\). Moreover, we analyzed the long-term \(\text{NDVI}_{iG}^S\) trends (figure 2(c)) for different vegetation types (figure 2(d)) across the TP. On the annual time scale, the regional average \(\text{NDVI}_{iG}^S\) shows a significant upward trend over the
past 40 years (trend = 0.0011 year⁻¹; figure 2(c)), which agree well with the findings of Duan et al. (2021) and Teng et al. (2021). According to the vegetation map (figure 1(a)), alpine meadow is the dominant vegetation across the TP and is mainly distributed in most of the central and eastern areas (covering about 23% of the total region). Our results show that 65% of forests, 62% of shrubs, 72% of meadows, and 72% of steppes show significantly upward trends in NDVI$_{GS}$ (figure 2(d)). Forests and shrubs tend to have higher NDVI$_{GS}$ values than steppe (figure 2(d)). In comparison, the greening trend of alpine meadows is generally slightly larger than that of alpine steppe, which is in agreement with the finding of a prior study (Zhang et al. 2014). In a nutshell, vegetation across the TP has generally experienced a greening trend during the past four decades. These results are also supported by the findings of the recent studies (Duan et al. 2021; Teng et al. 2021).

3.2. Spatial patterns of trends in climatic drivers
To figure out the climatic drivers of the general greening trend across the TP, we also investigated the spatial changes in the six climatic drivers during the growing season. It is obvious that warming has occurred in more than 95% (89% with $p < 0.05$) of the TP from 1982 to 2018 with a regional average warming trend of 0.54 °C decade⁻¹ (figure 3(a)). The longwave radiation also shows a predominantly increasing trend across 93% (86% with $p < 0.05$) of the TP (figure 3(b)). In contrast, the shortwave radiation demonstrates a predominantly decreasing trend across 78% (55% with $p < 0.05$) of the TP (figure 3(c)). Around 86% of the vegetated areas experience an increasing trend in precipitation, while decreasing trends in precipitation appear in a small area of the southwestern and southeastern forest and shrub regions (figure 3(d)). As for wind speed, we observed a downward trend at 63% (42% with $p < 0.05$) of the region, which is mainly covered by alpine steppe and alpine meadow (figure 3(e)). In terms of VPD, it displays a predominantly upward trend over 82% of the region (50% with $p < 0.05$; figure 3(f)), while decreasing trends appear in the 18% of the TP, 49% of which show significant downward trends and are mainly located in the forest regions. In summary, TP has experienced substantial climatic changes over the past four decades with an overall significantly upward trend in air temperature, precipitation, VPD, and longwave radiation, along with a general downward trend in shortwave radiation and wind speed.

3.3. Dominant climatic drivers to NDVI$_{GS}$ multidecadal changes
Figure 4 shows the relative contributions of different climatic drivers to the long-term changes in NDVI$_{GS}$ quantified by the partial least squares regression and standardized multivariate linear regression methods. Only VIP values for longwave radiation, air temperature, precipitation, and VPD among the six climatic drivers are larger than 1 (figure 4(a)), suggesting these climatic drivers have relatively stronger explanatory significance to the changes in NDVI$_{GS}$. Therefore, we selected these four drivers to further explore their contributions to NDVI$_{GS}$ in the following analyses. Based on the analyses of partial least squares regression and standardized multivariate linear regression, air temperature exerts the most extensive influence on NDVI$_{GS}$ and dominantly controls NDVI$_{GS}$ dynamics over around 62% of the TP region (figures 4(b)–(c)). Meanwhile, precipitation and VPD serve as the dominant controlling factor for NDVI$_{GS}$ over 19% and 12% of the TP region, respectively, which are mainly located in the southwestern TP, covered by alpine steppe and alpine meadows, and have relatively high elevations (figure 1(b)) and a cold-arid climate (figure S1 available online at stacks.iop.org/ERC/4/045007/mmedia)). Although longwave radiation dominantly impacts NDVI$_{GS}$ over 7% of the TP, mainly located in southern shrub areas, one should note that longwave radiation is highly correlated with air temperature and may serve as the second dominant factor or one of the top driving factors in these areas with air

Figure 3. Spatial patterns of trends in (a) air temperature ($T$), (b) longwave radiation ($L_{rad}$), (c) shortwave radiation ($S_{rad}$), (d) precipitation ($P$), (e) wind speed ($u_2$), and (f) VPD in the growing season from 1982–2018. The insets are the relative frequency (%) of the trend amplitude within the corresponding range indicated by the color bar. Regions marked with dots have statistically significant ($p < 0.05$) values.
temperature as the dominant impacting factor (Xie et al. 2021). In other words, temperature-dominated regions may also bear the substantial impacts of longwave radiation.

3.4. Partial correlations between NDVI_GS and climatic drivers

To further assess the impacts of the three main climatic drivers (air temperature, precipitation, and VPD) on vegetation interannual variability over the TP, we further analyzed the partial correlations between NDVI_GS and three climatic drivers. Air temperature is found to be positively correlated with NDVI_GS over 81% (58% with \( p < 0.05 \)) of the TP (figure 5(a)), indicating that warming is the main driver of vegetation greening during the past four decades over the TP. In contrast, the effect of precipitation on vegetation has a pronounced spatial heterogeneity (figure 5(b)). The positive correlation between NDVI_GS and precipitation appears over 37% of the TP (31% with \( p < 0.05 \)), which is mainly distributed in the western TP, while the negative correlation occurs over 56% of the TP (12% with \( p < 0.05 \)), mainly in the southeastern and central areas (figure 5(b)). More specifically, the negative precipitation-NDVI_GS correlation is found mainly for alpine meadows and shrubs, while the positive correlation is mainly for cold alpine steppe. Similar findings on the correlation patterns between NDVI_GS and temperature and between NDVI_GS and precipitation were also reported by Zhang et al. (2021b) with a study period from 1982 to 2015. In addition, VPD is negatively correlated with NDVI_GS across 58% (32% with \( p < 0.05 \)) of the TP, while the significantly negative correlation mainly appears in the southern and eastern regions (figure 5(c)).

To further sort out the relative contributions of climatic factors on vegetation changes for different vegetation types during the growing seasons across the study region, we derived the compositions of different dominant correlations types between NDVI_GS and climatic factors for the four major vegetation types across the TP (figure 6). Clearly, air temperature has a predominantly positive correlation with NDVI_GS for all of the four vegetation types (figures 5(a) and 6), indicating that most of the TP is still temperature-limited and warming can consequently enhance vegetation growth. However, precipitation has a predominantly negative correlation with NDVI_GS for the forest type (about 18% of the total cases; figure 6(b)), while it is dominantly positively correlated with NDVI_GS for the steppe (about 20% of the total cases; figure 6(c)). Note that forests on the TP are mainly located in the south and southeast of the TP (figure 1(a)), which are water-surplus regions. Therefore, further increases in precipitation may impose an adverse impact on forest growth in this region likely due to corresponding increased cloudiness. In contrast, VPD has a predominantly negative correlation with NDVI_GS for shrubs, forests, and meadows (figure 6) mainly due to the VPD stressing effect on the stomatal openness.
4. Conclusions and discussion

Although several recent studies investigated the vegetation dynamics over the TP during the recent 30 years using satellite NDVI data in the context of rising temperature and precipitation (Li et al 2020, Teng et al 2021, Zhang et al 2021b). However, the possible mechanisms underlying the observed NDVI spatiotemporal patterns remain unclear. Therefore, we systematically investigated how various climatic factors impact the growing-season vegetation dynamics for different vegetation types during the past four decades using multiple attribution analysis methods. Our results reveal that NDVI_GS shows a significant upward trend over the past 40 years (trend = 0.0011 year$^{-1}$; P < 0.01) (figures 2(b)–(c)), which is consistent with the finding of Teng et al (2021). However, trends in NDVI_GS show apparent spatial heterogeneity over the TP with higher growth rates in forests (trend = 0.012 d$^{-1}$; P < 0.01) and shrubs (trend = 0.009 d$^{-1}$; P < 0.01) located in the east and southeast than in alpine steppe (trend = 0.003 d$^{-1}$; P < 0.01) and alpine meadow (trend = 0.006 d$^{-1}$; P < 0.01) (figure 2(d)).

Additionally, air temperature, precipitation and VPD serve as the dominant climatic factor affecting the long-term trend in NDVI_GS in 62%, 19%, and 12% of the TP, respectively, making them as the top three climatic factors explaining the NDVI_GS changes from 1982 to 2018. Our findings are supported by many independent recent studies in several aspects. Results from the partial correlation method corroborate that air temperature positively influences the interannual variability of NDVI_GS across 81% of the TP, especially in the eastern part (figure 5(a)). This is in a good agreement with the findings of Zhang et al (2021b), who reported that increasing temperature is the main driver to enhance the vegetation growth across the TP. One possible reason is that warmer temperatures may lead to longer growing seasons, higher photosynthetic rates, and increased biomass (Ni, 2000). Furthermore, temperature can determine the nutrient availability for plants by influencing the litter decomposition rate (Wu et al 2011). It is interesting to note that air temperature has depressed vegetation greening in the north of the TP (figure 5(a)). This might be related to the physical mechanism that evapotranspiration can be largely enhanced with higher temperatures and correspondingly strengthen water deficits in growing season (Che et al 2014, Zhang et al 2015, Cheng et al 2018). In addition, precipitation plays a varying role in plant growth in different areas of the TP. In particular, our results highlight that increased precipitation constraints rather than promotes vegetation growth in the eastern sub-humid areas (about 56% of the TP), which are not water-limited (Wang et al 2020); higher precipitation are usually associated with larger cloud cover, resulting in less net radiation for vegetation in these areas. For these sub-humid areas, the weakening effect of increased precipitation on vegetation growth may relate to the accompanying decreased temperature and surface incident shortwave radiation as precipitation increases (Munne-Bosch and Alegre, 2004, Liu et al 2016). Moreover, extreme precipitation can even cause landslides or other disasters.

Figure 6. Compositions of dominant correlations types between NDVI_GS and climatic factors, including air temperature (red), precipitation (green), and VPD (blue), for (a) shrubs, (b) forests, (c) steppes, and (d) meadows.
which further exerts adverse effects on vegetation growth. VPD dominantly controls vegetation dynamics in 12% of the TP that are mainly covered by alpine steppe and meadow (figures 1(a) and 4(b)); these areas are characterized by high elevation, cold environment, and seasonal to year-round frozen soil. Possible mechanisms are that higher VPD could induce stomatal closure and thus reduce vegetation photosynthesis (Eamus et al. 2013, Novick et al. 2016, Konings et al. 2017). The hydraulic burden would also increase by enhanced evapotranspiration rates under higher VPD (Breshears et al. 2013, Liu et al. 2016), which restricts plant growth.

Our results also highlight that the responses of NDVIGS to changes in climatic factors show apparent spatial heterogeneity and biome-dependency with alpine steppe most sensitive to change in precipitation and forests, shrubs, and alpine meadows more vulnerable to warming-induced increases in VPD. Alpine steppe has the most active positive response to precipitation, while other vegetation types mainly show a negative correlation with precipitation (figure 6). It is clear that alpine grassland has the lowest annual mean temperature and growing-season precipitation (figure S2), but it has the highest wind speed; the nature of cold-dry conditions in these regions can explain why vegetation in these areas have a higher sensitivity to precipitation. Our results also show that the effect of VPD on NDVIGS may vary among different vegetation types on the TP. Increased VPD was found to greatly threaten the growth of forests, shrubs, and alpine meadows over the past decades over 58% of this region. However, increased VPD has both positive and negative effects on the alpine steppe. This finding generally agrees well with the previous studies (Ding et al. 2018, Kimm et al. 2020). The study of Yuan et al. (2019) shows that the NDVI under warm climate may be more vulnerable to the negative impact of VPD. Finally, our results suggest that vegetation tends to maximize the utilization of climatic benefit and minimize the climatic risks over the TP. In humid areas, vegetation is more sensitive to temperature, thus maximizing thermal benefits. In drier regions, maximizing water use causes NDVIGS to be more sensitive to precipitation (Shen et al. 2015). In summary, this study provides a comprehensive investigation on how growing-season NDVI and its climatic drivers have changed over the 1982–2018 period and how climatic changes impact growing-season NDVI dynamics across the TP. The findings of this study have a valuable implication on how future climate changes can further impact vegetation dynamics in this region.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

Author contribution

Conceptualization, Ke Zhang and Xi Li; Methodology, Xi Li, Ke Zhang, and Xin Li; Software, Xi Li; Visualization, Xi Li; Writing—original draft, Xi Li and Ke Zhang; Writing—Review & Editing, Ke Zhang, Xi Li, and Xin Li; Project Administration, Ke Zhang.

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