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Characteristics and trends of rainstorm activities and their impacts on seasonal vegetation variations in coastal China

Jianguo Li a,*, Yi Wang b,c, Lili Liu a, Shi-Yong Yu a,∗

a School of Geography, Geomatics, and Planning, Jiangsu Normal University, Xuzhou, Jiangsu 221116, China
b Department of Geography and School of Global Studies, University of Sussex, Falmer, Brighton BN1 9RH, UK
c Department of Earth System Science, Institute for Global Change Studies, Tsinghua University, Beijing 100084, China

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ABSTRACT

Within the context of global climate changes, rainstorms have increasingly become one of the important ecological interferences limiting plant growth and population turnover. However, due to the significant spatial and temporal variability of rainstorms, determining their quantitative relationships with plant growth at some longer temporal and larger spatial scales is challenging. In this study, the relationships between rainstorm changes and vegetation activities are explored by analysing the spatial and temporal correlations between the normalized difference vegetation index (NDVI) and rainstorm frequency on the coast of China during the period of 1982–2015. Our results show that: (1) Both rainstorm frequency and vegetation activities tend to increase gradually over the study period. The impact of rainstorms on vegetation in the northern part of the study area is greater than that in the southern part. (2) Overall, rainstorms have a significant (p < 0.1) negative impact on vegetation activities in the northern parts of the study area, especially during the summer months. Furthermore, the negative impact of rainstorms on vegetation in autumn tends to be strengthened into the future. (3) Rainstorms overall have significant and negative impacts on shrub, coniferous forest, broad-leaved forest during the growing season. The strong-impact seasons and locations of rainstorm on vegetation activities identified by our study can dramatically benefit future ecosystem and water resource management in coastal China.

1. Introduction

Rainstorm represents a high-impact meteorological event and an important manifestation of future climate changes, which is generally defined as a large amount precipitation (exceeding a specified threshold) occurring within a short period of time (Groisman et al., 1999). Additionally, rainstorm can also result in significant ecological losses (Nesbitt et al., 2015), thereby influencing plant growth and ecosystem services. Notably, vegetation activities are the main pathway to regional food production and carbon sequestration in the terrestrial ecosystems (He et al., 2016; Li et al., 2018b; Pan et al., 2022), which are controlled by many factors that exhibit remarkable spatiotemporal variability (Gao et al. 2019; Li et al., 2018a; Li et al., 2019; Li et al., 2020a; Ugboje et al., 2017; Su et al., 2018; Zhou et al., 2015). Within the context of global climate change, ever-increasing extreme climate events will play a key role in vegetation activities and the monthly variation of vegetation activities tends to be intensified (Li et al., 2020b). The increasing uncertainty and vulnerability of vegetation activities will become a huge obstacle for better predicting the future global carbon cycle dynamics (Fang et al., 2019; Li et al., 2020b). Currently, the influencing mechanism of the factors driving vegetation activities can be determined using mechanistic models, such as VISIT (Ito and Inatomi, 2012), OCN (Zaehle and Friend, 2010), ORCHIDEE (Ducoudré et al., 1993), JULES (Best et al., 2011), CLM4.5 (Oleson et al., 2004), ISAM (Jain et al., 1994), LPJ (Smith et al., 2001) and LPX (Sitch et al., 2003), etc. However, these models generally are insufficient to explore the relationships between extreme climate events (e.g., rainstorm or drought) and vegetation activities. Therefore, quantitatively determining the relationship between rainstorms and vegetation activities may help inform policy about ecosystem management in the future.

The long-term variations of vegetation is mainly driven by natural factors, such as soil water, temperature, and atmospheric radiation (Mao et al., 2018), among which precipitation is still one of the key drivers for plant growth over a longer timescale (e.g., a few decades) (Li et al., 2020a; Nemani et al., 2003; Zhao et al., 2019). The intensity and frequency of precipitation not only affect water distribution, but also...
significantly drive the changes in temperature, atmospheric radiation, and land surface cover. In fact, during rainstorms, an increased cloudiness in the atmosphere can remarkably reduce solar radiation (Arch-ernicholls et al., 2015). Furthermore, the variation in evapotranspiration as induced by rainstorms may result in a complicated effect on surface temperature and energy budget (Zhao and Khalil, 1993). Both models and observations have demonstrated an increasing trend in heavy rainstorms worldwide since 1901, especially in tropical and temperate zones (Asadieh and Krakauer, 2014) and the same trend has been found in USA (Ashouri et al., 2015). It is noteworthy that global vegetation activities show a significantly rising tendency as well (Liu et al., 2015). Previous studies have shown that China’s vegetation activities have been enhanced in the past 30 years (1982–2012) at a rate of 0.00029/yr (NDVI indicator), especially in the farmland and forestland zones of eastern China (Liu et al., 2018, Li et al., 2020a). Also, one study (Liu et al., 2018) has revealed that El Niño and solar activity are the two main driving factors of vegetation activities at a longer time scale.

Rainstorms generally have a negative effect on vegetation activities (Pradhan and Mohanty, 2013). For instance, excessive rainfall can lead to soil compaction and increase the supersaturation of soil water, which in turn can restrict vegetation growth (Howe, 2007). Furthermore, severe flooding caused by rainstorms may result in oxygen deficiency, thereby limiting the aerobic respiration, energy production and nutrient loss (i.e., leaching) as well as increasing the risk of pest and diseases of vegetation (Hirschi et al., 2012; Pradhan and Mohanty, 2013; Ramos and Martínez-Casasnovas, 2010). Tan et al. (2009) has reported that the supersaturated soil caused by rainstorms can give rise to an anomalous consequence to vegetation activities and in some cases, can even kill plants. Supersaturated soil water can also reduce soil pH and Eh (electric potential) values as well as increase the phytotoxic by-products that may overall threaten the survival of plants (Pradhan and Mohanty, 2013). Compared with temperature, precipitation and radiation, rainstorms are an important ecological factor influencing vegetation activities. However, the extent and distribution of rainstorms usually vary remarkably in both time and space. Therefore, vegetation responses to rainstorms are hard to observe at a shorter timescale and a larger spatial scale, and quantitatively determining the relationship between rainstorms and vegetation activities is difficult. More importantly, the negative impacts of rainstorms on plants are significant and more attention needs to be paid due to their associated ecological risks (Ding et al., 2007; Kawabata et al., 2001; Schultz and Halpert, 1993; Tang et al., 2016; Wang, 2017).

Currently, there are many criteria for rainstorm identification and classification. Due to the significant difference in climatic conditions, these criteria dramatically differ worldwide. The ClimDex model is the main tool for determining rainstorm occurrence, which has been extensively used around the world (Ramirez-Sanchez et al., 2016; Wu and Huang, 2016). However, its criterion to define extreme precipitation is some relatively low value (i.e., 25 mm/24 h), which is significantly lower than the actual climatic conditions of China. In eastern China, monsoon and heavy precipitation are the dominant climate modes, especially in coastal areas and during the summer season. Thus, in this study, we have applied a new criterion for rainstorm classification. In addition, the coastal areas of eastern China are the main ecological function zones with a relatively high level of vegetation coverage and species richness. Therefore, determining the relationship between rainstorms and vegetation activities in coastal China is an important task to promote regional ecosystem management. Nevertheless, how and to what extent rainstorms affect vegetation activities is still not well understood (Deng et al., 2018; Liu et al., 2018).

Therefore, in this study, monthly Global Inventory Modelling and Mapping Studies-NDVI (GIMMS-NDVI 3 g) and daily precipitation during the period from 1982 to 2015 were retrieved from 190 meteorological stations, in order to explore the trends of rainstorm frequency and NDVI variations and to quantitatively identify their relationships at the pixel level (each pixel covers an 8-km by 8-km square grid). The objectives of this work were: (1) to establish the characteristics and trends of rainstorm frequency and the NDVI in coastal China, and (2) to identify the relationships between rainstorm variations and vegetation activities at each grid cell using statistical statistics.

2. Study area

The coast of China comprises 15 provinces, covering an area of 0.95 million km² with a coastline of 8000 km long (see Fig. 1). The study area is also characterized by the developed economics, which contributes to nearly 60% of the total GDP of China (Zhao et al., 2014). In this area, rainstorms and typhoons frequently occur in the summer due to the influence of the East Asian summer monsoon. All zones in the study area have records of typhoon occurrence, especially on the southeast coast, including Hainan, Guangdong, Taiwan, Fujian, Guangxi, and Zhejiang provinces. Climate zones of this area are highly diverse. For example, a tropical climate zone is found in provinces of Guangdong and Hainan. Climate zone across Guangxi to Jiangsu provinces is the subtropical climate zone. The areas to the north of Jiangsu province is characterized by a temperate climate (Fig. 1).

The main landforms in the study area are plains and low-lying hills. The plains are mainly located to the north of the Hangzhou Bay, including the Liaohe Plain, the North China Plain, and the Middle-Lower Yangtze Plains, the majority of which is below 200 m in elevation. In addition, the elevation of areas south to the Yangtze River (including the south Jiangsu Plain, the Zhejiang-Fujian Hills and the Guangdong-Guangxi Hills) is generally below 500 m, showing an undulating landform, and they are broadly staggered with valleys, plains, and basins. To the west of Hebei province, north of Guangdong and Fujian provinces, plateaus, mountains, and hills are widely distributed.

The vegetation types of the study area include coniferous forests (~146398.3 km², 11.12%), broad-leaved forests (~60408.52 km², 4.59%), coniferous and broad-leaved mixed forests (~112769.6 km², 8.56%) as well as cultivated vegetation (~574410.7 km², 43.62%), shrubs (~326614.9 km², 24.8%), grasslands (~46876.84 km², 3.56%), and swamps (~10480.12 km², 0.8%). In the coastal areas, coniferous forests are the main vegetation type, which encompasses temperate coniferous forests and subtropical coniferous forests, the former is generally found to the north of Shandong province and the latter is mainly distributed in Zhejiang, Fujian, Guangdong, and Guangxi provinces. Broad-leaved forests are widely spread in Liaoning, Hebei, Shandong, Jiangsu, and Zhejiang provinces. However, coniferous and broad-leaved mixed forests are mainly located in southeastern Liaodong Peninsula. Moreover, cultivated vegetation is generally found in coastal areas. Liaoning, Hebei, Shandong, and north Jiangsu provinces mainly cultivate dry crops and deciduous orchards. To the south of Jiangsu province, the cultivated vegetation has been converted to rice, evergreen orchard, and subtropical–tropical economic forests. Grasslands are mainly located in hills of southwest Liaoning, west Hebei, Guangdong, Guangxi and Hainan provinces. Swamps occur generally in coastal regions, the northern part of which develops into cold temperate and temperate swamps with a typical vegetation of reeds. Mangrove forests are mainly distributed in the southern part of coastal areas. Grasslands are generally and dispersively found in the west and northwest of Hebei province as well as in the west of Liaoning province.

3. Data sources and statistical methods

Extensive studies have revealed that the NDVI is an effective and sensitive indicator of vegetation activities (Gao et al., 2019; Kawabata et al., 2001; Wen et al., 2016). The GIMMS-NDVI 3 g (Global Inventory Modelling and Mapping Studies-NDVI, NDVI) dataset (https://ecocast.arc.nasa.gov/data/pub/gimms/3g/v1/) covers a longer period (from 1982 to 2015) and has a higher accuracy due to the successive sensors. Therefore, it was employed in our study to infer vegetation activities. This dataset was developed by Tucker et al. (2005) at National Aeronautics and Space Administration (NASA) based on the Advanced Very
High Resolution Radiometer (AVHRR) launched by National Oceanic and Atmospheric Administration (NOAA). The NDVI dataset encompasses a 34-year (totally 408 months) period spanning from 1982 to 2015 and covers the whole study area with an 8 × 8 km grid box and semimonthly (15-day) temporal resolution. Datasets for precipitation, radiation, and temperature are retrieved from National Meteorological Information Center of China (https://data.cma.cn/). Rainstorm frequency and precipitation in five time intervals defined as spring (March-May), summer (June-August), autumn (September-November), winter (December-February), and the growing season (April-October) were produced to explore the relationships between rainstorm and vegetation activities (Piao et al., 2006). Before conducting spatial statistics, the anomalies of storm frequency, temperature, precipitation, and NDVI were calculated using the following formula:

\[
T_i = \frac{M_i - M_{i-1}}{\text{mean}(M_{i-1})}
\]

where, \(T_i\) is the anomaly of rainstorm frequency, temperature, precipitation, and NDVI, \(M_i\) and \(M_{i-1}\) are the rainstorm frequency, temperature, precipitation and NDVI in month \(i\) and \(i-1\), respectively, mean \((M_{i-1})\) is average values of all month \(i-1\) during the study period (1982–2015). This method can be used to reduce the influences of human activities and to improve the accuracy of our results (Bastos et al., 2013).

Partial correlation was used to explore the relationship between storm frequency anomaly and NDVI anomaly at pixel level, which was calculated from the formula (Jukić and Deničuk, 2018):

\[
r_{12,345} = \frac{r_{12,34} - r_{15,34}r_{25,34}}{\sqrt{1 - r_{15,34}^2} \times \sqrt{1 - r_{25,34}^2}}
\]

where, \(r_{12,345}\) is the third order partial correlation of each grid cell between the NDVI anomaly (factor 1) and rainstorm frequency anomaly (factor 2), without the influences of temperature (factor 3), precipitation (factor 4) and radiation (factor 5). \(r_{12,34}, r_{15,34}\) and \(r_{25,34}\) are the second order partial correlation of different combination factors as listed above, respectively.

The slope obtained from one-dimensional element regression was used to indicate the trends of the four factors (i.e., storm frequency, temperature, precipitation and NDVI) at the pixel level. It was defined as:

\[
K_{\text{slope}} = \frac{\sum_{i=1}^{n} (x_i - \bar{x}) (y_i - \bar{y})}{\sum_{i=1}^{n} (x_i - \bar{x})^2}
\]

where \(K_{\text{slope}}\) is the trend of different factors; \(x_i\) is year \(i\); \(y_i\) is annual temperature, precipitation, rainstorm frequency, and NDVI of year \(i\); \(\bar{x}\) and \(\bar{y}\) are the mean values of \(x_i\) and \(y_i\) respectively; \(n\) is the study period (here \(n = 34\)). The greater the \(K_{\text{slope}}\) is, the more rapid is the increase of

Fig. 1. Map showing the location of study area and main vegetation types. Red dots indicate meteorological stations used in this study.
different factors. A multiple linear regression model was constructed to determine the quantitative relationship between rainstorm frequency anomaly and the NDVI change at each pixel. The equation takes the following form:

\[ y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \epsilon \]  

(4)

where \( \beta_{0,4} \) are coefficients of multiple linear regression; \( x_{1-4} \) are anomalies of rainstorm frequency, temperature, precipitation and radiation respectively. \( y \) is the NDVI anomaly. For example, \( \beta_1 \) has been allocated to each grid based on the model. The negative \( \beta_1 \) represents a constraint effect, whereas the positive \( \beta_1 \) represents a stimulating effect of rainstorm frequency on NDVI variation.

4. Results and discussion

4.1. Characteristics and trends of rainstorm activities

As shown in Fig. 2a, rainstorm frequency along the coast of China during 1982–2015 ranges from 0 to 13 times per year, with an average value of twice per year. The higher rainstorm frequency is located in the northern and central part of the study area, including Jiangsu, Shandong, and Hebei provinces. The rainstorm frequency in some above-mentioned regions is up to 5 times per year. These regions are located mainly in eastern Shandong Peninsula, southern Hebei, northern Jiangsu, Shanghai, northern Zhejiang, eastern and central Guangdong, and northern Guangxi provinces. However, the lower rainstorm frequency is mainly found in Hainan, Leizhou Peninsula, southern Guangxi, northern and central Fujian, western Liaoning, and northern Hebei provinces. In general, the northern and central sectors of the study area exhibit the higher rainstorm frequency, especially in northern Jiangsu and Shandong provinces. This is mainly due to the strongly transitional climate zones from the subtropical to the temperate monsoonal climates. Monthly precipitation tends to be concentrated and distributed unevenly, showing that summer precipitation continues to increase gradually from south to north in the study area.

As concluded by previous studies, the ClimDex model was an effective tool and usually adopted to calculate indices of climate extremes and to monitor and detect climate changes (Gujree et al., 2017; Ramírez-Sánchez et al., 2016). A total of 27 indices can be obtained using the ClimDex model, of which 11 indices (e.g., continuous wet days and storm days) related to precipitation were retrieved (Bürger et al., 2012). The index of storm days (denoted hereafter as R25) is similar to the rainstorm frequency in our study. In the ClimDex model, the R25 index was defined as the total days when the daily precipitation is larger than 25 mm/24 h. Different from the ClimDex model, in our study, the threshold value for R25 was given as 50 mm/24 h based on China’s climate conditions.
NDVI values were probably caused by port construction and the Hainan, Zhejiang and Guangxi provinces, where NDVI can be as high as relatively high values occur in the southern part including Fujian, the mean NDVI rising from 0.52 in 1982 to 0.56 in 2015 (Fig. 4). A positive impact on the increasing regional NDVI and winter NDVI over the study period. Fig. 2c-d show that the total number of rainstorms tends to increase sharply from 171 times in 1982 to 433 times in 2015 and most of the rainstorms occurred in summer.

4.2. Characteristics and trends of NDVI

Fig. 3 shows that NDVI in the study area has a significant increasing trend from 1982 to 2015. Moreover, the annual ranges of NDVI variations tend to decline from 0.35 in 1996 to 0.23 in 2014. The dominant factor contributing to this reduction is that the winter NDVI continues to increase, while the summer NDVI remains nearly stable (Fig. 3). Within the context of global warming, winter temperature shows an increasing trend in the recent 50 years, especially in the Northern Hemisphere (Reichert et al., 2004; Yao et al., 2012). Thus, the increasing NDVI in subtropics contributes a large proportion to the increasing NDVI in the study area in winter. Moreover, the ecological restoration program, land-use management (e.g., increased agricultural activities and harvested area) and the atmospheric nitrogen deposition may have exerted a positive impact on the increasing regional NDVI and winter NDVI over a longer timescale (Chen et al., 2019; Jia et al., 2016).

In the study area, the mean of the NDVI shows an upward trend, with the mean NDVI rising from 0.52 in 1982 to 0.56 in 2015 (Fig. 4). Relatively high values occur in the southern part including Fujian, Hainan, Zhejiang and Guangxi provinces, where NDVI can be as high as 0.87 (Fig. 4a). The higher NDVI value mainly occurs in mountainous and hilly regions, due likely to the lower intensity of human interferences (Li et al., 2012; Li et al., 2018a). Relatively low NDVI values are located in west and southeast Hebei and south Jiangsu provinces as well as the Yangtze River and Pearl River Deltas. Actually, the farming-pastoral zone is mainly located in western Hebei provinces where annual precipitation merely ranges from 200 mm to 400 mm. In the past 30 years, the conversions from forestslands to farmlands and overgrazing have significantly destroyed the natural ecosystems in western Hebei province, which further led to lower NDVI values with an average of -0.1. However, in southeast Hebei and north Shandong provinces, the lower NDVI values were probably caused by port construction and the increasing reclamation of tidal flat-lands driven by human activities (Sun et al., 2015).

As shown by the results of the K_slope method (Fig. 4b-c), NDVI values in most parts of the study area tend to increase gradually from 1982 to 2015 with a mean rate of 0.0002/yr. NDVI is the key indicator of vegetation activities. The increasing trend of NDVI values in this study is consistent with the enhanced vegetation activities in the Northern Hemisphere (Zhao and Running, 2010). More importantly, the increasing vegetation activities may prompt the carbon sequestration of terrestrial ecosystems and mitigate global warming, thereby further reducing the potential risk of losses caused by rainstorms (Piao et al., 2009; Wang et al., 2015). Simultaneously, the grid cells with a significant and positive K_slope of the NDVI values are dispersive and mainly occur in southeastern Liaoning, southeastern Hebei, northern Jiangsu, northern Fujian, and western and central Guangdong provinces (Fig. 4c). The changes of economic patterns and the ecological conservation program due to the higher GDP of these regions are also responsible for the increasing NDVI values (Hu and Xia, 2019). Nevertheless, the significant and negative K_slope of the NDVI values can be found in northeast Liaoning and southeast Guangxi provinces, where the rapid development of agriculture and unreasonable mineral resources exploitation may have significantly reduced the NDVI values.

4.3. Trends of precipitation, temperature, and radiation

Fig. 5 shows that precipitation, temperature and solar radiation in the study area tend to increase from 1982 to 2015. As shown in Fig. 5a, monthly precipitation generally continues to increase slowly. Precipitation is influenced by many factors and shows a region-dependent feature. Deng et al. (2018) have reported that over 50% of all meteorological stations in China show an increasing trend in both the intensity and frequency of precipitation, especially in southwestern China. Many previous studies suggested that the southeast monsoon has a significant impact on precipitation in spring and summer (Liu and Wang, 2011; Wang et al., 1998; Wang and Yan, 2014). Moreover, in northwestern China, precipitation exhibits an increasing trend mainly because of plenty of atmospheric moisture supplies from the Caspian Sea delivered by the westerly winds. However observational data revealed a decreasing trend of precipitation in northern and northeastern China mainly driven by the Indian Ocean dipole mode index (DMI) variations and the water cycle of the northwestern Pacific Ocean (Deng et al., 2018; Ye, 2014).

Monthly mean temperature exhibits a periodic feature (e.g., seasonal variation) with a range between −0.2 °C and 27°C. On the extreme value of temperature, summer temperature tends to increase gradually (Fig. 5b). Although extremely low temperature was found in recent years (e.g., −0.2 °C in 2010), temperature has an increasing trend over the study period, which is probably explained by the cyclic fluctuations of climate and human activities (Hu et al., 2018). The trend of precipitation is similar to that of temperature, but has a greater range (2–260 mm/month) of variations.

Similar to temperature, solar radiation also shows an increasing trend with a large monthly variation (172.3–586.7 kwh/m²/month) and its increasing trend is beneficial to promoting vegetation activities (Fig. 5c). Global observation has demonstrated that solar radiation has been increasing from late 1980s (namely, brightening phase) (Ohmura, 2009). And, this brightening period (first brightening phase) is followed by the decreasing trend lasting to late 1980s, known as the global dimming, which finally translates into the second brightening phase in many regions of the world. These decadal variations are to great extent caused by aerosol and cloud fluctuations (Ohmura, 2009; Wild, 2009). Therefore, the increasing solar radiation in the study area may likely be caused by combined impacts of human activities and climate change.

4.4. Relationships between the anomalies of rainstorm frequency and the changes in the NDVI

According to Eqs. (2)–(4), the partial correlation and multiple
regression coefficients ($\beta_1$) between rainstorm frequency anomaly and the NDVI anomaly at each pixel were calculated (Fig. 6). The significant and positive multiple regression coefficient $\beta_1$ can be found in Jiangsu, western Fujian, and central Guangxi provinces (Fig. 6a). Compared with Hebei province, multiple regression coefficient $\beta_1$ in Jiangsu is generally higher. However, the significant and negative multiple regression coefficient $\beta_1$ mainly occurs in the Beijing-Tianjin-Hebei region, central Zhejiang and north Guangxi provinces, showing a remarkably negative effect of rainstorm frequency on the NDVI anomaly. The main reason is that, although agriculture in Hebei province needs massive water to relieve drought in spring, spring rainstorms seldom occur in this area. Moreover, the increasing spring NDVI was generally driven by the rising temperature rather than precipitation (Piao et al., 2006).

In summer (June–August, Fig. 6b), a significant and positive partial correlation between rainstorm frequency anomaly and the NDVI anomaly can be found in south and west Hebei, north Liaoning, Hainan, Guangdong and north Guangxi provinces, showing a remarkably positive impact of rainstorms on the NDVI. Although rainstorm can destroy and limit vegetation activities at a shorter timescale, abundant precipitation caused by rainstorm is still beneficial to vegetation survival out of drought at a longer timescale. In Guangxi and Guangdong provinces, the positive partial correlation can be explained by the increasing NDVI caused by ecological restoration and the increasing rainstorm frequency. Notably, the karst landscape is wide-spread in Guangxi province (Wang et al., 2018). As a result of the shallow soil layer, it is not in favor of water and nutrient conservation (Feng et al., 2016). Therefore, rainstorm is possible to promote plant growth. Differing from the positive partial correlation, rainstorm overall has a significant negative impact on the NDVI in major parts of the study area including the Shandong Peninsula, north Jiangsu, western Guangxi and the south foot of Mount Wuyi in Fujian province (Fig. 6b).

Based on the regression coefficient, in case of other factors remaining...
Fig. 5. The trend of monthly averaged precipitation (a), temperature (b) and radiation (c) in the study area. (The grey shades and blue line are the same as in Fig. 2.).
Fig. 6. Relationships between rainstorm frequency anomaly and the NDVI anomaly for different seasons: a) Spring, b) Summer, c) Autumn, d) Winter, and e) Growing. For each season, we have shown three plots: 1) partial correlation between the rainstorm and NDVI (left), 2) multiple regression between the rainstorm and NDVI (central), and 3) the time series of rainstorm with the best-fit blue lines and grey shades (95% confidence interval, right).
constant, an increase of 0.01%–0.35% of the NDVI with an increase of 1% of rainstorm frequency in the northern part of study area, especially in Hebei and Liaoning provinces can be found (Fig. 6). However, a significant and negative multiple regression coefficient ($\beta_1$) was found in north Jiangsu and Shandong provinces, showing a decrease of 0.04%–0.45% of the NDVI with an increase of 1% of rainstorm frequency if other forces remain constant (significant negative effect).

In autumn (September-November, Fig. 6c), the areas where autumn NDVI correlates significantly and negatively with storm frequency are located in Hebei, northeast Fujian, and northeast Guangxi provinces, indicating that the increasing storm frequency will significantly reduce the autumn NDVI in the study area. Because winter (December–February, Fig. 6d) is the non-growing season for vegetation, the statistical results show a less ecological significance of the NDVI in winter, especially in the northern part of eastern China. In contrast, winter rainstorm results in a significant and positive impact on the NDVI variation in south Jiangsu, north Zhejiang, and central Guangxi provinces.

Our study reveals that the influences of rainstorms on vegetation activities vary seasonally (Fig. 6e). The results show an increasing rainstorm frequency that may have exerted a significant and negative impact on the NDVI variations in summer and autumn in the central study area. However, significant and positive impacts of rainstorms were found in the northern part of study area, including Hebei and Liaoning provinces. In addition, as shown in Fig. 6c, rainstorm frequency in autumn over the study period tends to increase but it keeps stable in summer, suggesting that the inhibiting effects of autumn rainstorms on vegetation activities probably tend to strengthen and even exceed that in summer. Overall, rainstorms in summer and autumn significantly reduce the NDVI along the east coast of China.

During the growing season (April-October, Fig. 6e), rainstorm frequency shows an increasing trend at a relatively low rate (Fig. 6e), which implies that the negative effect of rainstorms on vegetation activities is likely to increase in the future. However, at a larger spatial scale, the dominate factors (including soil oxygen deficiency, nutrient loss and limiting aerobic respiration) driving the negative effect of rainstorm on vegetation activities are unclear due to the different vegetation types and controlling environmental factors. Therefore, long-term in-situ observation of vegetation response to rainstorms is an important and effective work to answer this question (Reis et al., 2018).

**Fig. 6.** (continued).
4.5. The different performance of mean multiple regression coefficient $\beta_1$ for different vegetation types

As shown in Fig. 7, the mean multiple regression coefficient ($\beta_1$) varies remarkably for different vegetation types. In the growing season, a negative multiple regression coefficient $\beta_1$ was found for shrub, coniferous forest and broad-leaved forest, suggesting that rainstorm overall has a remarkable and negative effect on them. Nevertheless, for swamp, grassland, coniferous and broad-leaved mixed forest and cultivated vegetation, rainstorm generally exerts a positive impact on them. In particular, rainstorm in growing season can greatly promote grasses growth, with a mean multiple regression coefficient $\beta_1$ of 0.026. In the study area, grasslands are mainly distributed in northern and northwestern parts, where abundance water delivered by rainstorm can significantly relieve drought in growing season (Cai et al., 2015). In addition, rainstorms occurring in summer and autumn overall can cause a remarkable and negative effect on most of vegetation types in the study area, especially grasslands. However, it is noteworthy that spring rainstorm can generally enhance the activities of most vegetation types, except for the coniferous and broad-leaved mixed forests and swamp (Fig. 7). In particular, a high mean multiple regression coefficient $\beta_1$ was found for broad-leaved forest in spring, which indicates that rainstorms are beneficial to the growth of the broad-leaved forests in this season. As revealed in Fig. 7, the herbaceous vegetation is generally more sensitive to rainstorm than the woody vegetation (Brandt et al., 2019).

4.6. Different performance of mean coefficient $\beta_1$ in different regions

Fig. 8 shows that the mean multiple regression coefficient ($\beta_1$) in different provinces and seasons is different significantly. In spring (Fig. 8), the mean multiple regression coefficient ($\beta_1$) of the whole area is 0.001, which implies that rainstorms generally have a positive impact on the spring NDVI (March–May). When other factors (e.g., precipitation, temperature and radiation) remain stable, the NDVI values tend to increase by 0.001% with an increase of 1% of rainstorm frequency. However, a negative multiple regression coefficient $\beta_1$ (-0.01) was found in Beijing, Tianjin, Shanghai, Hebei, Guangdong and Zhejiang provinces with a negative. A positive multiple regression coefficient $\beta_1$ mainly occurs in Liaoning, Shandong, Jiangsu, Fujian and Guangxi provinces. The multiple regression coefficient $\beta_1$ is the highest in Fujian, indicating that spring rainstorm in Fujian can significantly promote the NDVI. For the whole study area, the mean multiple regression coefficients $\beta_1$ is positive (0.01), showing that spring rainstorm generally can enhance vegetation activities (Fig. 8). In summer, the mean multiple regression coefficient $\beta_1$ is -0.005, indicating that summer NDVI tends to decline by 0.005% with an increase of 1% of rainstorm frequency if the influences of other factors can be excluded. Spatially, a negative multiple regression coefficient $\beta_1$ occurs in the major parts of the study area, including Beijing, Tianjin, Shandong, Jiangsu, Fujian and Guangxi provinces. The lowest multiple regression coefficient $\beta_1$ was found in Shandong and Jiangsu provinces, indicating a remarkable negative effect of rainstorms on vegetation activities. Nevertheless, a positive impact of summer rainstorms was found in Liaoning, Hebei, Shanghai, Guangdong and Hainan provinces, especially in Shanghai. Compared with summer, autumn mean multiple regression coefficient $\beta_1$ in many provinces tends to decrease. However, as indicated by Fig. 6c, the impact of autumn rainstorms probably may increase continuously. Furthermore, the negative effect of summer rainstorms in Jiangsu turned to a positive effect in autumn. Notably, autumn mean multiple regression coefficient $\beta_1$ in Hebei and Guangdong has changed from positive to negative value, indicating that the constraint effect of rainstorms tends to strengthen. Summer mean multiple regression coefficient $\beta_1$ in many provinces is significantly higher than that of other seasons, demonstrating that summer rainstorms can generally result in a negative effect on vegetation activities, especially in Shandong and Jiangsu provinces. For the growing season, a higher mean multiple regression coefficient $\beta_1$ was found in Jiangsu, showing that rainstorms generally can promote vegetation activities in this region. In general, rainstorms in the northern part of the study area can promote vegetation activities, whereas in the southern part of the study area, the influence of rainstorms tends to be negative (Fig. 8). For the whole region, the mean multiple regression coefficient $\beta_1$ of the growing season is -0.002, indicating that the NDVI tends to decrease by 0.002% with an increase of 1% of rainstorm frequency. Furthermore, the impact of rainstorms on the NDVI changes in the northern part of the study area is greater than that in the southern part.

4.7. Other factors that may influence rainstorm and vegetation activities

Within the context of global warming, precipitation continues to increase gradually (Dore, 2005). In eastern Asia, extreme precipitation is mainly controlled by monsoon (Ying and Ding, 2010). Deng et al. (2018) reported that the intensity and frequency of precipitation in China during the period of 1965–2015 increased significantly and showed a remarkable spatial variability predominantly driven by the Dipole Mode Index (DMI). Previous study showed that precipitation changes in the

Fig. 7. The mean multiple regression coefficient $\beta_1$ for different vegetation types for the whole study region from 1985 to 2015.
Yangtze River Delta (YRD) during the past 60 years were mainly influenced by large-scale monsoon (Pei et al., 2018). Therefore, in the study area, rainstorm frequency is probably determined by monsoon. Furthermore, aerosol and solar radiation can significantly affect the stability of atmosphere, which further result in precipitation changes (Vargo et al., 2018). For instance, the increasing atmosphere aerosol may reduce precipitation significantly, which performs as a positive feedback loop (Zhao et al., 2006). However, in a regional scale, micro-landform and human activities might play a critical role in rainstorm frequency changes (Grant et al., 2017). Speculated from the distribution of higher rainstorm frequency events in the study area, climate pattern and monsoon might have greater impact on the frequency of rainstorm events.

Many studies have suggested that precipitation and temperature dominantly control the variability of the NDVI (Gu et al., 2018; Li et al., 2020a; Piao et al., 2006; Wang et al., 2003; Ding et al., 2018). In the growing season, the relationship between NDVI anomaly and rainstorm frequency changes differs among different places and seasons. Previous studies revealed that spring temperature generally has a significant impact on NDVI (Gu et al., 2018; Li et al., 2015). Spatially, the NDVI is more sensitive to the variations of temperature and precipitation in North China than that in South China (Cui and Shi, 2010). In addition, a temporal delay in vegetation variation (NDVI) to climate changes was observed, which is called the “lag effect” (Piao et al., 2006). On vegetation NPP (Net primary productivity), a significant lag effect usually exists in forest ecosystems, and a lag time of 1–4 years has been determined among Pinaceae (Anderegg et al., 2015). However, the lag effect of semi-arid ecosystems may be 16–19 months long (Ling et al., 2016). The length of the lag effect of vegetation activities differs significantly among different types of vegetation and climate (Li et al., 2020a). In China’s temperate grasslands, a 3-month-long lag effect has been observed (Li et al., 2020a; Piao et al., 2006). Nevertheless, a lag of <30 days has been identified in eastern China (Cui and Shi, 2010).

5. Conclusions

In the study area, a set of spatial statistic methods have been employed to explore the characteristics and trends of rainstorm and their impacts on NDVI change in eastern coastal China. The main conclusions are as follow:

(1) During the period of 1982–2015, the mean rainstorm frequency in coastal China has tended to increase gradually. And, higher rainstorm frequency mainly occurred in the northern and the middle parts of the study area. Most of rainstorms in the study area generally occurred in summer. Overall, the vegetation activities in the study area have shown a upward trend, and of which the higher value mainly occurred in the southern part of the study area. This indicates that the vegetation responses to rainstorm is not homogeneous. Therefore, further studies are needed to understand the reasons behind this phenomenon.

(2) Rainstorms generally have produced significant impacts on vegetation activities and exhibited remarkable spatial-temparal variability. Overall, rainstorms in summer and autumn could significantly reduce vegetation activities in the study area. However, a positive impact has been found in northern parts of the study area, mainly located in Hebei and Liaoning provinces. In spring season, rainstorms show significant and positive impacts on the vegetation activities if other factors (e.g., precipitation, temperature and solar radiation) remain the same. In summer season, rainstorms have significant and negative impacts on the vegetation activities in the northern part of Jiangsu and southern part of Shandong provinces. Currently, the vegetation activities is most sensitive to rainstorm frequency changes in the summer. Furthermore, the increasing autumn rainstorm frequency may have significant and negative impacts on the future vegetation activities. This indicates that the vegetation responses to rainstorms have significant seasonal and spatial variations. Similar future studies should be carefully designed to pay attention to those variations.

(3) In terms of different vegetation catalogues, rainstorms overall have given rise to negative impacts on shrub, coniferous forest, broad-leaved forest during the growing season, nevertheless positive impacts have been determined for other vegetation types (e.g., swamp, grassland, cultivated vegetation and coniferous and broad-leaved mixed forest). In this context, more efforts should be made in promoting water resource management for shrub, coniferous forest and broad-leaved forest in summer and autumn in the northern parts of the study area.

CRediT authorship contribution statement

Jianguo Li: Conceptualization, Methodology, Data curation, Software, Writing – original draft. Yi Wang: Writing – review & editing. Lili
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References

Anderegg, W.R., Schwalm, C., Biondi, F., Anderegg, L.D., 2015. Large-scale shifts in vegetation productivity in response to large-scale warming. Global Biogeochem. Cycles 28, 1–15.

Brandt, M., Hiernaux, P., Rasmussen, K., Tucker, C.J., Wigneron, J.-P., Diouf, A.A., 2015. Aerosol-radiation-cloud interactions in a regional coupled model: the effects of convective parameterization and resolution. J. Geophys. Res. Atmos. 120, 10,047–10,060.

Bustos, A., Running, S.W., Gouveia, C., Trigo, R.M., 2013. The global NPP dependence on ENSO: La Niña and the extraordinary year of 2011. J. Geophys. Res.: Biogeosci. 118, 1247–1255.

Cui, L., Shi, J., 2010. Temporal and spatial response of vegetation NDVI to temperature over North hemisphere. Acta Geogr. Sinica 57, 505–512.

Ding, J., Yang, T., Zhao, Y., Liu, D., Wang, X., Yao, Y., Peng, S., Wang, T., Piao, S., 2018. Increasingly important role of atmospheric aridity on Tibetan alpine grasslands. Geophys. Res. Lett. 45, 2852–2859.

Ding, M., Zhang, Y., Liu, L., Wei, Z., Wang, Z., Bai, W., 2007. The relationship between NDVI and precipitation on the Tibetan Plateau. J. Geophys. Res. 102, 259–268.

Dore, M.H., 2005. Climate change and changes in global precipitation patterns: what do we know? Environ. Int. 31, 1167–1181.

Dube, K., Nhamo, G., 2018. Climate variability, change and potential impacts on tourism: an inductive study of tourists’ perceptions. Ocean Travel & Tourism 11(2), 27–38.

Hu, J., Cheng, H., Shi, J., 2016. Description of the joint UK Land Environment Simulator (JULES), model description Part 1: energy and water fluxes. Geosci. Model Dev. 9, 767–789.

Jain, A., Wuebbles, D., Kheshgi, H., 1994. Integrated science model for assessment of climate change. Lawrence Livermore National Lab, CA (United States).

Jia, Y., Yu, G., Gao, Y., He, N., Wang, Q., Jiao, C., Yan, Z., 2016. Global inorganic nitrogen dry deposition inferred from ground and space-based measurements. Sci. Total Environ. 518, 1810–1819.

Jukic, D., Menicucci, E., 2019. Investigation of spatial and temporal variability of groundwater flow process by using higher-order partial correlation functions: theoretical considerations. Geophysical Research Abstracts. EGU General Assembly 2019, Austria.

Kawabata, A., Ichii, K., Yamaguchi, Y., 2001. Global monitoring of interannual changes in vegetation activities using NDVI and its relationships to temperature and precipitation. Int. J. Remote Sens. 22, 1377–1382.

Li, J., Liu, J., Li, Y., Liu, L., 2012. Spatial and Temporal Characteristics of Terrestrial Vegetation Activities and Their Influencing Factors in Chongqing Syndrome. Land Degrad. Dev. 33, 65–72.

Li, J., Wang, W., Wang, H., Li, Y., Zhang, Z., Li, L., 2018. The effect of urbanization on productivity of terrestrial ecosystems – taking Jiangsu Province as an example. Resources 40, 32–43 (In Chinese).

Li, J., Yuan, F., Zhao, D., Zhang, Z., Pu, L., L., 2018b. The driving factor framework of soil organic carbon evolution in coastal beaches. Scientia Geographica Sinica 38, 580–589 (In Chinese).

Li, J., Zou, C., Li, Q., Xu, X., Zhao, Y., Wang, Z., Zhang, Z., Liu, L., 2019. Effects of urbanization on productivity of terrestrial ecosystems based on remote sensing: a case study in Jiangsu, Eastern China. J. Geophys. Res.: Biogeosci. 114, 1–10.

Li, J., Wang, Y., Liu, L., 2020a. Responses of the terrestrial ecosystem productivity to droughts inside China. Front. Earth Sci. 6, 100015.

Li, J., Zhang, S.Y., Liu, L., 2020b. The direct and indirect effects of the variability of terrestrial ecosystem productivity in China during the last two decades. Land Degrad. Dev. doi:10.1002/ldr.3580.

Ling, H., He, B., Chen, A., Wang, H., Liu, L., Liu, A., Chen, Z., 2016. Drought dominates the interannual variability in global terrestrial net primary production by controlling semi-arid ecosystems. Sci. Rep. 6, 14639.

Liu, K., Li, W., 2015. Effects of urbanization on productivity of terrestrial ecological systems based on remote sensing: a case study in Southern China. Environ. Monit. Assess. 187, 165.

Liu, X., Wang, Y., 2011. Contrastings impacts of spring thermal conditions over Tibetan plateau on late-spring to early-summer precipitation in southern China. Adv. Atmos. Sci. 28, 123–132.

Mao, D., Wang, Z., Wu, B., Zeng, Y., Luo, L., Zhang, B., 2018. Land degradation and restoration in the arid and semiarid zones of China: quantified evidence and implications from satellites. Land Degrad. Dev. doi:10.1002/ldr.3151.

Nemani, R., Keeling, C., Hashimoto, H., Wofsy, S., Tucker, C., Myneni, R., Running, S., 2003. Climate-Driven Increases in Global Terrestrial Net Primary Production from 1982 to 1999. Science 300, 1560–1563.

Nesbitt, S.W., Cifelli, R., Rudeva, S., 2015. Storm Morphology and Rainfall Characteristics of TRMM Precipitation Features. Mon. Weather Rev. 143, 2709–2721.

Ohmura, A., 2009. Observed decadal variations in surface solar radiation and their causes. J. Geophys. Res.: Atmos. 114, 1–22.

Pan, X., Min, J., Li, J., Gao, M., Wang, Y., Tang, J., 2018. Measuring green development level at a regional scale: framework, model, and application. Environ. Model. Softw. 104, 343–351.

Zhang, Z., Liu, L., Pu, L., Shi, J., 2018. Soil erosion rates in two karst peak-cluster depression basins of northwest Guangxi, China. Atmos. Res. 204, 168–177.

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Su, B., Huang, J., Fischer, T., Wang, Y., Kundzewicz, Z.W., Zhai, J., Sun, H., Wang, A., Smith, B., Prentice, I.C., Sykes, M.T., 2001. Representation of vegetation dynamics in the model. Global Change Biol 9, 161–174.

Reichert, T., Simonsen, L., Sharma, A., Pardo, S., Fedson, D., Miller, M., 2004. Influenza virus type A and B seasonal activity surveillance and trends in the United States. J. Epidemiol. 160, 492–502.

Reis, S.A., Ellsworth, L.M., Kauffman, J.B., Wronski, D.W., 2018. Long-Term Effects of Fire on Vegetation Structure and Predicted Fire Behavior in Wyoming Big sagebrush Ecosystems. Ecosystems 22, 257–265.

Schulze, P.A., Halpert, M.S., 1993. Global correlation of temperature, NDVI and precipitation. Adv. Space. Res. 13, 277–280.

Sitch, S., Smith, B., Prentice, I.C., Arneth, A., Bondeau, A., Cramer, W., Kaplan, J.O., Levis, S., Lucht, W., Sykes, M.T., 2003. Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model. Global Change Biol 9, 161–185.

Smith, B., Prentice, I.C., Sykes, M.T., 2003. Representation of vegetation dynamics in the modelling of terrestrial ecosystems: comparing two contrasting approaches within European climate space. Global Ecol Biogeogr 10, 621–637.

Su, B., Huang, J., Fischer, T., Wang, Y., Kundzewicz, Z.W., Zhai, J., Sun, H., Wang, A., Zeng, X., Wang, G., Tao, H., Gemmer, M., Li, X., Jiang, T., 2018. Drought losses in China might double between the 1.5 °C and 2 °C warming. Proc. Natl. Acad. Sci. 115, 10605–10605.

Sun, Z., Sun, W., Tong, C., Zeng, C., Yu, X., Mou, X., 2015. China’s coastal wetlands: conservation history, implementation efforts, existing issues and strategies for future improvement. Environ. Int. 79, 25–41.

Tan, S., Zhu, M., Zhang, K., Dang, H., Zhang, Q., 2009. Response and adaptation of plants to flooding stress. Chinese Journal of Ecology 28, 1871-1877.(In chinese).

Tang, Z., Ma, J., Li, Z., Peng, H., Liang, J., 2016. Temporal and spatial changes of vegetation in the upper reaches of the Shiyan River Basin and their responses to regional climate. Geography and Geoscience Information Science 32,116-120.(In Chinese).

Tucker, C.J., Pinzon, J.E., Brown, M.E., Slayback, D.A., Pak, E.W., Mahoney, R., Vermote, E.F., Saleous, N.E., 2005. An extended AVHRR 8 km NDVI dataset compatible with MODIS and SPOT vegetation NDVI data. Int. J. Remote. Sens. 26, 4485-4498.

Ubajje, S.U., Odeh, I.O.A., Bishop, T.F.A., Li, J.L., 2017. Assessing the spatio-temporal variability of vegetation productivity in Africa: quantifying the relative roles of climate variability and human activities. Int. J. Digital Earth 10, 879–900.

Vargo, L.J., Galeywsky, J., Rupper, S., Ward, D.J., 2018. Sensitivity of glaciation in the arid subtropical Andes to changes in temperature, precipitation, and solar radiation. Global Planet. Change 163, 86–96.

Wang, J., Rich, P.M., Price, K.P., 2003. Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA. Int. J. Remote. Sens. 24, 2345-2364.

Wang, M., Chen, H., Zhang, W., Wang, K., 2018. Soil nutrients and stoichiometric ratios as affected by land use and lithology at county scale in a karst area, southwest China. Sci Total Environ 619–620, 1299–1307.

Wang, Q., Ding, Y., Jiang, W., 1998. Asian monsoon activity and its relationship with precipitation in the Chinese mainland. J. Appl. Meteorol. 11,85-90.(In chinese).

Wang, X., 2017. Study on the extreme climate change along the coast of China and its impact on NDVI, Yantai,China (PhD Thesis).

Wang, X., Piao, S., Xu, X., Cao, Z., Maeben, N., Myneni, R.B., Li, L., 2015. Has the advancing onset of spring vegetation green-up slowed down or changed abruptly over the last three decades? Global Ecol. Biogeogr. 24, 621–631.

Wang, Y., Yan, F., 2014. Characteristics of regional variation and interdecadal variation of precipitation in China from 1960 to 2010. Progress in Geography 33,1354-1363 (In Chinese).

Wen, Z., Wu, S., Chen, J., Lii, M., 2016. NDVI indicated long-term interannual changes in vegetation activities and their responses to climatic and anthropogenic factors in the Three Gorges Reservoir Region. China. Sci. Total Environ. 574, 947–959.

Wild, M., 2009. Global dimming and brightening: A review. J. Geophys. Res.: Atmos. 114 doi:10.1029/2008JD011470.

Wu, C., Huang, J., 2016. Projection of climate extremes in the Zhujiang River basin using a regional climate model. Int J Climatol 36, 1184–1196.

Yang, M., Zhang, W., 2019. Orographic Effects of Geomorphology on Precipitation in a Pluvial Basin of the Eastern Tibetan Plateau. Water 11, 250.

Yao, J., He, X.Y., Li, X.Y., Chen, W., Tao, D.L., 2012. Monitoring responses of forest to climate variations by MODIS NDVI a case study of Hun River upstream, northeastern China. Eur. J. For. Res. 131, 705–716.

Ye, J.S., 2014. Trend and variability of China’s summer precipitation during 1955–2008. Int. J. Climatol. 34 (559-566).

Ying, S., Ding, Y.H., 2010. A projection of future changes in summer precipitation and monsoon in Asia. Sci. China: Earth Sci. 53, 284–300.

Zaehle, S., Friend, A.D., 2010. Carbon and nitrogen cycle dynamics in the O-CN land surface model: 1. Model description, site-scale evaluation, and sensitivity to parameter estimates. Global Biogeochem Cy 24, GB1005.

Zhang, Z., Zhang, C., Hou, H., Wang, Y., 2016. Application examples of leaf precipitation level tracing (GB/T28592-2012). Modern agricultural science and technology 223-223 (In Chinese).

Zhao, C., Tan, X., Tan, Y., 2006. A possible positive feedback of reduction of precipitation and increase in aerosols over eastern central China. Geophys. Res. Lett. 33, 229–239.

Zhao, M., Running, S.W., 2010. Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. Science 329, 940–943.

Zhao, W., Zhu, Z., Chen, C., Wang, G., Feng, X., Liu, S., 2018. Contributions of climatic factors to inter-annual variability of vegetation index in northern China grasslands. J. Clim. https://doi.org/10.1175/JCLI-D-18-0587.1.

Zhao, W., Zhao, Z., Wang, W., 2014. Changes in the economic spatial pattern of the eastern coastal areas of China. Econ. Geogr. 34, 14–18 (In Chinese).

Zhou, J., 2016. Study on the extreme climate change along the coast of China and its impact on NDVI, Yantai,China (PhD Thesis).

Zhao, W., Khalil, M.A.K., 1993. The Relationship between Precipitation and Temperature in the Yangtze River basin. Progress in Geography 16, 340–348.

Pradhan, C., Mohanty, M., 2013. Submergence Stress: Responses and adaptations in crop plants. pp. 331-357.

Ramos, M.C., Martinez-Casanovas, J.A., 2010. Impacts of annual precipitation extremes on soil and nutrient losses in vineyards of NE Spain. Hydrolog. Processes 23,224-235.

Ramírez-Sánchez, H., Guadalupe, M.G., Ullas-Godínez, H., Meulenent-Pena, A., García-Concepción, J., Gutiérrez, J.A., 2016. Observed and future changes in the temperature of the state of Jalisco, Mexico using Climdex and PRECIS. Am. J. Clim. Change 5, 38.