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The response of China's wetland vegetation to climate changes

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Abstract: Wetland vegetation dynamics are of vital importance for comprehending changes in ecosystem structure. Under the background of global climate change, it is still unclear the change trends of wetland vegetation in China, and whether there are differences between the response of wetland vegetation and non-wetland vegetation to climate change. Based on Global Inventory Modeling and Mapping Studies (GIMMS) NDVI3g, NOAA Vegetation Health Products (VHP) and climate data, this study explored the response of wetland vegetation to climate change in China from 1981 to 2015. The results show that: 1) NDVI of wetland vegetation in China shows a downward trend on the whole after the year of 2004. 2) In water-limited zones, wetland vegetation NDVI is positive correlated with precipitation; while in temperature-limited zones, it is positive correlated with temperature. 3) El Nino and La Nina may affect wetland vegetation NDVI. The greater impact of La Nina phenomenon than El Nino phenomenon is the possible reason for the upward trend of wetland vegetation NDVI, while the greater impact of El Nino phenomenon than La Nina phenomenon may be the reason for the downward trend of NDVI. 4) The response of wetland vegetation and non-wetland vegetation to climate change is significantly different. Non-wetland vegetation responds more significantly to climate change than wetland vegetation.

Keywords: Wetland vegetation; Climate change; Trend analysis; Wavelet transform; AVHRR Normalized Difference Vegetation Index (NDVI)

1. Introduction

Wetland vegetation is the totality of all plant communities in a wetland area (Cui and Yang, 2006). It plays an important role in water storage, regulation of flood flows and maintenance of regional water balance. Vegetation grown in wetlands can also purify environment by integrating environmental factors (Powicki, 1998). In the past few decades, climate change has affected all continental ecosystems (Gao et al., 2016; Lindsey, 2008), one of which is that it has a profound impact on the growth and function of vegetation (Peng et al., 2013). With the frequent occurrence of extreme phenomena such as El Nino and La Nina in recent years, understanding the response of wetland vegetation to climate change is important for predicting changes in wetland vegetation (Shen et al., 2019).

Some previous studies have analyzed the correlation between vegetation and climate variables (precipitation and temperature) under different location and regional conditions (Schultz and Halpert, 1993; Ichii et al., 2002). However, the timeliness and resolution of the data used of these studies is low, the method is relatively single, and the influence of El Nino and La Nina phenomenon is not considered and there are few details about China. At present, some scholars have explored the response of vegetation in different regions to climate change across China. The influence of climate change on vegetation varies significantly with different climatic zones. For example, zones with rising temperature promotes the growth of vegetation include the Wet Area (WA) of Central Subtropical (CS), WA, Semi-Wet Area (S-WA), Semi-Arid Area (S-AA) and Arid Area (AA) of Plateau Temperate Zone (PT) (Guo et al., 2017; Li et al., 2018; Liu et al., 2017; Zeng et al., 2018). The zones in which temperature rise inhibits vegetation are S-WA and AA of Warm Temperate Zone (WT) (A et al., 2017; Wang, 2018). In addition, zones with increasing precipitation promotes vegetation development include S-AA and AA of Medium Temperature Zone (MT) and PT, S-AA of Plateau Sub-frigid Zone (PS-f) (Chen et al., 2016; Du et al., 2015a; Guo et al., 2017; Li et al., 2018; Liu et al., 2017; Wei, 2018; Yang et al., 2016; Yang et al., 2018). As a unique vegetation type, wetland vegetation keeps its roots moist all year round, which leads to its inconsistent response mode to climate change with other vegetation types. In the context of global climate change, some scholars give recommendations on wetland management and restoration (Erwin, 2009). Some previous studies have focused on the response of specific wetland vegetation types (seagrasses,

tidal marsh plants, mangroves and so on) to climate change (Short et al., 2016). However, few studies analyze the response of overall wetland vegetation to climate change at the national scale in long time term. Therefore, how does climate change impact on wetland vegetation? Are there differences in the response of wetland vegetation and non-wetland vegetation to climate change?

The objectives of this study are to: (1) analyze the change trend of wetland vegetation in China from 1981 to 2015; (2) explore the responses of wetland vegetation to climate change; (3) compare the response of wetland vegetation and non-wetland vegetation to global climate change.

2. Data sources and methods

2.1 Indices and data sources

We select NDVI as the indicator to reflect the change of wetland vegetation. NDVI is the most commonly vegetation index using to characterize vegetation growth and coverage by remote sensing method (Vrieling et al., 2014). As an important ecological parameter to characterize vegetation, NDVI is widely used in the study of vegetation dynamics. Meanwhile, the relationship between NDVI and global climate changes had been widely confirmed both regionally and globally (Ji and Peters, 2003; Prasad et al., 2007; Y et al., 2012). The value of vegetation NDVI ranges from 0 to 1. The higher the NDVI value, the better the growth and coverage of vegetation. The NDVI data derived from GIMMS NDVI3g, which was developed from Advanced Very High Resolution Radiometer (AVHRR), with temporal resolution of 15 days and spatial resolution of 1/12°. It has been calibrated for cloud testing, sensor shifting and eliminates the effects of many factors, such as the solar zenith angle (Piao et al., 2011). Data from AVHRR cover the time series from 1981 to 2015 and supply the only long-term updated large-scale dataset of vegetation greenness (Pinzon and Tucker, 2014). The period selected in this research is 1981 to 2015.

Vegetation Condition Index (VCI) is employed to calculate the relative difference between NDVI and the historical minimum NDVI of the same pixel. It can detect drought and measure its impacts on vegetation (Kogan and Sullivan, 1993). Therefore, VCI could reflect the environmental conditions of wetland. The value of VCI ranges from 0 to 100. Generally, if VCI is less than 40, it indicates that the wetland condition is poor; if VCI is greater than 40 and less than 70, it means that the wetland condition is moderate; if VCI is greater than 70, it shows that the wetland condition is good (Kogan and Sullivan, 1993). VCI is derivative of NOAA VHP data. NOAA VHP data is a long-term sequence dataset newly developed by the US Oceanic and Atmospheric Administration. Its temporal resolution is 7 days and its spatial resolution is 4 km.

Climate indicators we choose are temperature and precipitation. The near-surface temperature and ground precipitation rate can reflect the temperature and precipitation of the growing environment of wetland vegetation. China's regional ground meteorological elements dataset were downloaded from the Cold and Arid Science Data Center and were used to analysis climate change. It is a set of near-surface meteorological and environmental element reanalysis dataset developed by Yang Kun et al (He and Yang, 2011). Its temporal resolution is 3h and its spatial resolution is 0.1°. Among the seven data types it contains, we select near-surface temperature and ground precipitation rate.

In addition, we use national wetland classification data to extract wetland vegetation samples. This dataset was developed based on Landsat and CBERS-02B imagery circus 1978, 1990, 2000 and 2008 across China through manual visual interpretation and a large quantity of field verifications (Niu et al., 2012). They were synthesized from a spatial resolution of 30m to 1 km. We extracted coastal marshes and inland marshes in the national wetland classification data for selecting samples. In details, the coastal

marshes include mangrove plants, reeds and so on, which are intertidal saltwater swamps with vegetation coverage of 30% or more; inland swamps are permanent or seasonal swamps, including apes, herbs, shrubs, forest swamps, oasis wetlands and spring wetlands with water surface exposed area less than 30%.

At last, we use the latest China climate zoning dataset (Zheng et al., 2010) as the climate zoning data, which used the daily meteorological observation data of 609 meteorological stations from 1971 to 2000. It divides China into 12 temperature zones, 24 dry-wet zones and 56 climate zones.

2.2 Methods

2.2.1 Selection of wetland vegetation samples

Considering the hydro-dynamics of wetlands, we firstly screen out the overlapping marsh patches (including coastal marshes and inland marshes) with area of being more than 9 km² from the four national wetland maps (Niu et al., 2012). Then we extract the geometric central points of these patches. The geolocation of those points was used to extract the NDVI value of wetland vegetation from the GIMMS NDVI3g data. To ensure that the extracted points belong to the wetland vegetation type, we check them one by one based on the temporal trajectory changes in NDVI value along the past 35 years (Figure 1) and remove the samples that do not belong to the vegetation (they may be flooded for a period of time). In this way, a total of 117 stable wetland vegetation (SWeV) samples were obtained nationwide (Figure 2). Detailed information on the specific climatic zoning of SWeV samples can be found in Table S1.

2.2.2 Ordinary least squares linear regression

We calculate the average change rate of indicator factors in the growing season by ordinary least squares linear regression method (OLS):

$$Y(t) = \alpha_0 + \beta_0 t + \varepsilon \quad (1)$$

where α_0 and β_0 are the fitting intercept and slope, respectively. Indicators represent VCI, near-surface temperature and ground precipitation rate. The months selected for the growing season are May to September. We use the two-tailed T test to test the trend significance level of the regression equation. If the obtained P is no more than 0.01, the trend is extremely significant.

The slope of the indicator trend line can be calculated by:

$$SLOPE = \frac{n \times \sum_{i=1}^n i \times Ave_{seasonal_i} - (\sum_{i=1}^n i)(\sum_{i=1}^n Ave_{seasonal_i})}{n \times \sum_{i=1}^n i^2 - (\sum_{i=1}^n i)^2} \quad (2)$$

where n is the number of years studied, i is the serial number of the year, and $Ave_{seasonal_i}$ is the average of the indicator factors for the i -year growing season. If $SLOPE$ is positive, the indicator factor shows an increasing trend in n years; otherwise, it shows a decreasing trend. If $SLOPE$ is equal to zero, there is no significant change trend in the indicator factor during the study period.

2.2.3 Wavelet transform method

Wavelet transform is a signal analysis method (Li et al., 2010) that can automatically adapt to time-frequency analysis requirements (Ning et al., 2004). It is widely used in time series feature extraction (Praveen et al., 1997; Liu 2012; Sang et al., 2013; Kędra et al., 2017; Zhang et al., 2018a). Liu (2012) uses the wavelet transform to extract trend items of hydrological time series. Meanwhile, wavelet transform is compared with other traditional methods (Trend Regression Method, Moving Average

Method and Mann-Kendall Test Method) which can extract trend items of time series in his article. The conclusion is that the theory of extracting trend items of time series based on wavelet transform is better. Wavelet transform can decompose the time series into a high-frequency part and a low-frequency part. High frequency can be used to extract the random item and the periodic item of time series, while the remaining low-frequency part can be used to extract trend items of time series (Zhang et al., 2018a).

The wavelet transform is to shift (b) the wavelet basis function $\psi(t)$ and then inner product with the time series $x(t)$ at different scales (a):

$$WT_x(a, b) = a^{-\frac{1}{2}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt, a > 0 \quad (3)$$

Its form in the frequency domain is (Daubechies 1992):

$$WT_x(a, b) = \frac{a^{-\frac{1}{2}}}{2\pi} \int_{-\infty}^{\infty} X(\omega) \psi^*(a\omega) e^{+j\omega b} d\omega \quad (4)$$

Where $\psi(\omega)$ and $X(\omega)$ are the Fourier transforms of $\psi(t)$ and $x(t)$, respectively.

When applying wavelet transform to extract features of time series, wavelet basis function and decomposition level should be determined. The wavelet basis function is related to whether it has regularity, orthogonality, symmetry, vanishing moment and tight support. The decomposition level is determined based on the complexity of the signal. The more complex the signal is, the more decomposition layers should be selected (Zhang et al., 2014).

In this paper, wavelet transform is mainly used to extract trend term of time series. The selected wavelet basis function is db_8 wavelet with lower compactness and higher vanishing moment. The time series of the study is the half-month wetland vegetation NDVI in 35 years, so the signal is relatively complex. At this time, the decomposition level is selected as 8 layers. The low-frequency information a_8 is used to obtain the inter-annual variation trend of SWeV NDVI.

2.2.4 Correlation Analysis

Correlation analysis studies whether there is a certain dependency relationship between phenomena, and then explores the relevant direction and extent. Its calculation formula is:

$$R_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (5)$$

Where R_{xy} is the correlation coefficient of the variables x and y , x_i is the value of NDVI of i -year growing season, $\bar{x}$ is the average of NDVI for the growing season of all study years, y_i is the value of climate factors of i -year growing season, $\bar{y}$ is the average of climate factors for the growing season of all study years.

We used partial correlation analysis to study the correlation between NDVI, near-surface temperature and ground precipitation rate. When studying the correlation between NDVI and temperature, the precipitation rate is set as the control variable. Moreover, we control temperature when studying the correlation between NDVI and precipitation rate. The formula for calculating the partial correlation coefficient is:

$$R_{xy.z} = \frac{R_{xy} - R_{xz}R_{yz}}{\sqrt{(1-R_{xz}^2)(1-R_{yz}^2)}} \quad (3)$$

Where $R_{xy.z}$ is the partial correlation coefficient of x and y under the control factor z .

3. Results

3.1 Spatio-temporal change trends of wetland vegetation NDVI

The growth condition and luxuriance of wetland vegetation in different temperature zones and wet-dry zones are variable, leading to significantly different wetland vegetation NDVI. The highest NDVI value being above 0.75 occurs in WA of Cold Temperate Zone (CT). Among all the wet-dry zones, the average value of wetland vegetation NDVI in AA is generally lower than the humid areas (Figure 3-a). Among all the temperature zones, the average value of wetland vegetation NDVI in CT, NS and CS is generally higher than the other zones (Figure 3-b). The corresponding wet-dry zones of the three temperature zones in China are all WA.

Through statistics (Table 1), we found that 82% of SWeV samples with $NDVI \geq 0.6$ were located in humid areas (WA and S-WA). Meanwhile, all SWeV samples with $NDVI \leq 0.3$ were located in dry areas (S-AA and AA). Therefore, we conclude that wetland vegetation NDVI is significantly related to the degree of wetness.

Wetland vegetation has an overall trend in long-term sequence, and there are differences in wetland vegetation changes in different regions. In this paper, we used wavelet transform to extract trend term of long time series of SWeV NDVI.

Firstly, the amplitude of NDVI was calculated to judge whether it's normal fluctuation. It is obtained by dividing the fluctuation value and the multi-year average value of NDVI. When the range of amplitude is within $\pm 10\%$, it is considered as normal fluctuation; otherwise, NDVI has obvious change trend in 1981-2015. We found that the NDVI changes of 7 SWeV samples were within the normal fluctuation range, and their locations were not concentrated. The NDVI of the remaining 110 SWeV samples showed a significant change trend.

Among the 110 research points that have significant variation trend, 83 of them have a turning point in the 35-year NDVI change trend. Most of the years in which the turning point is located are 2003 and 2004 (Figure 4-a). Meanwhile, NDVI of 80 SWeV points first increased and then decreased after the turning point (Figure 4-b). For the rest of SWeV samples, there is no turning point in NDVI change. Among them, NDVI of 19 SWeV samples showed a downward trend.

Overall, from 1981 to 2015, about 80% of the wetland vegetation NDVI showed a downward trend after the year of 2004, and about 10% of the wetland vegetation NDVI showed an upward trend after the year of 2003.

3.2 Spatio-temporal change trends of VCI of wetland vegetation

VCI can reflect the environmental status of wetland vegetation. If VCI is less than 40, it indicates that the wetland condition is poor (Kogan and Sullivan, 1993). When VCI shows an upward trend in long time series, and in the process of change, VCI increases from less than 40 to more than 40 (Type 2 in Figure 5), which means that the environment of wetland vegetation is significantly better. When VCI shows a downward trend in long time series, and it decreases from more than 40 to less than 40 (Type 3 in Figure 5), it means that the environment of wetland vegetation is significantly worse. When the trend of VCI is Type 1 (Figure 5), it means that the environment of wetland vegetation is better, but its impact on wetland vegetation is less than Type 2. Similarly, when the trend of VCI is Type 4 (Figure 5), it means that the environment of wetland vegetation is worse, but its impact on wetland vegetation is less than Type 3. Type 5 shows that the trend of VCI and the environment of wetland vegetation have not changed significantly.

Among the 117 research points, 40 of them whose VCI change trend is Type 2, which have a significantly better wetland environment. The wetland environment of 18 samples whose VCI change

trend is Type 3 is significantly worse. There is no significant trend in VCI in 16 samples. Generally, SWeV whose VCI change trend is Type 2 and Type1 accounts for 63% of the total. Such wetland vegetation environment is in a gradually improving state. Meanwhile, SWeV whose VCI change trend is Type 3 and Type 4 accounts for 23% of the total. Such wetland vegetation environment is in a worse state.

3.3 Climate change trends in locations corresponding to SWeV samples

We use the near-surface temperature of China's regional ground meteorological elements dataset to analyze the temperature changes in the regions corresponding to the SWeV. The SLOPE of near-surface temperature characterizes the changing trend of the temperature of the research point itself. Results show that the near-surface temperature of most sample points (110/117) show an upward trend (Figure 6-a), meaning the increasing temperature across those sample regions during the past 35 years. By contrast, the other seven sample points' near-surface temperature shows a downward trend.

We use the ground precipitation rate of China's regional ground meteorological elements dataset to analyze the precipitation changes at the corresponding regions of SWeV. The results show that the precipitation rate of most sample points (88/117) show an upward trend in the past 35 years (Figure 6-b), meaning the general increasing trend of precipitation across China. By contrast, the downward trend of the precipitation rate occurred across the other 29 sample points, which mainly distribute in WA of PS-f, S-WA of PT (83%) and WA of MT (69%).

3.4 Responses of wetland vegetation NDVI to climate variables

We calculate the partial correlation coefficient between NDVI and temperature (NDVI and precipitation rate) in the growing season. For those samples with a turning point in NDVI change, we calculate their correlations both before and after the turning point, respectively. The percentage of samples in each climate zone with different correlation relations are shown in Table 2.

The response of wetland vegetation NDVI to climate variables is obviously different among the various dry-wet climate zones. For all SWeV samples with significant change trend, wetland vegetation NDVI is negatively correlated with precipitation rate in wet climate zones (WA and S-WA), and the negative correlation is stronger in WA than in S-WA. However, wetland vegetation NDVI is positively correlated with precipitation in arid climate zones (S-AA and AA). By comparison, wetland vegetation NDVI is positively correlated with temperature for all sample points having the turning point in NDVI changing trend. The wetland vegetation NDVI negatively correlated with temperature was only in the S-AA samples without turning point.

The response of wetland vegetation NDVI to climate fluctuation is also different in various climate temperature zones. In temperature-limited zones (e.g., CT and PS-f), wetland vegetation NDVI is positively correlated with temperature (Table 2), and the more significant correlation is observed in the PS-f zone. However, no obvious correlation exists in the PT zone indicating the complexity of wetland vegetation changes to climate change. Due to the opposite trend of wetland NDVI change before and after the turning point in the WT zone, its NDVI change is positively correlated with temperature before the turning point and negatively correlated with temperature after the turning point. By contrast, the response of wetland vegetation NDVI to precipitation shows no obvious relationship among various temperature zones.

Wetland vegetation with high NDVI is negative correlated with precipitation, while wetland vegetation with low NDVI is positive correlated with precipitation (Table 1, Table 2). This is because the

wetland vegetation with high NDVI is mainly distributed in the area with high humidity. At the same time, the NDVI value of wetland vegetation is relatively low in the area with low humidity. Therefore, the increase of precipitation has an inhibitory effect on wetland vegetation with high NDVI, while it has a positive effect on wetland vegetation with low NDVI.

4. Discussion

4.1 The impact of climate change to wetland vegetation

El Nino and La Nina are effective indicators of global climate change. El Nino refers to the phenomenon of large-scale rising of water temperature that occurs in several years along the coast of Peru and on the eastern equatorial Pacific Ocean, while La Nina refers to the phenomenon of abnormal cooling of the water temperature on the ocean surface (Luo, 2000). The results show that there is a significant teleconnection between sea surface temperature in the eastern equatorial Pacific Ocean and air temperature in Northeast China, middle and lower reaches of Yangtze River, west and southwest of South China (Mo, 1989). At the time of El Nino, the climate of China was warm winter and cool summer, and the precipitation was more in the south than in the north. At the time of La Nina, the distribution of precipitation in China was more in the north than in the south, and the distribution of temperature was cold winter and hot summer (Zhang and Meng, 2005).

The high frequency part of time series obtained by wavelet transform corresponds to the period term of time series, and the low frequency part corresponds to the trend term. In the study, wavelet transform can also be used to remove the short period (seasonal change in the year) in the wetland vegetation NDVI time series change, and get the medium and long-term periodic change characteristics (inter-annual change characteristics), which have good corresponding relationship with El Nino and La Nina (Figure 7).

When the periodicity of wetland vegetation NDVI is corresponding to the seven El Nino years from 1981 to 2015 (a. 1982-1983; b. 1986-1987; c. 1991-1994; d. 1997-1998; e. 2002-2007; f. 2009-2010; g. 2014-2015) (Zhang et al., 2015), we find that the El Nino year is corresponding to the part of NDVI that shows a downward trend. Among the 117 wetland samples, the corresponding times of decreasing part of 69 samples' NDVI and the year interval of El Nino are more than or equal to 3, which means that El Nino phenomenon is the possible cause of the downward trend of wetland vegetation NDVI. We have calculated the corresponding situation of 7 El Nino year intervals and NDVI decreasing part, and found that there are 106 wetland vegetation samples' NDVI decreasing part corresponding to 2014-2015 El Nino, 62 corresponding to 2009-2010 El Nino. The corresponding quantity between El Nino year interval a, b, c, d, e and wetland vegetation samples with declining NDVI are 38, 30, 16, 31 and 12, respectively.

When the periodicity of wetland vegetation NDVI is corresponding to the six La Nina years from 1981 to 2015 (a. 1984-1985; b. 1988-1989; c. 1995-1996; d. 1999-2000; e. 2007-2009; f. 2011-2012) (Zhang et al., 2015), we find that the La Nina year is corresponding to the part of NDVI that shows an upward trend. Among the 117 wetland samples, the corresponding times of rising part of 69 samples' NDVI and the year interval of La Nina are more than or equal to 3, which means that La Nina phenomenon is the possible cause of the upward trend of NDVI of wetland vegetation. We have calculated the corresponding situation of 6 La Nina year intervals and NDVI rising part, and found that there are 64 wetland vegetation samples' NDVI rising part corresponding to 1984-1985 La Nina, 52 corresponding to 1988-1989 La Nina, 73 corresponding to 1999-2000 and 2011-2012 La Nina. The corresponding quantity between La Nina year interval c, e and wetland vegetation samples with rising NDVI are 28 and 17.

Combined with the inflexion of wetland vegetation NDVI in long time series (concentrated in 2002-2007), we found that: before the turning point, La Nina phenomenon has a greater impact on El Nino phenomenon, which may be the reason for the upward trend of wetland vegetation NDVI. According to the literature (Zhang et al., 2015), the intensity level of 2014-2015 El Nino phenomenon is higher than that of 2011-2012 La Nina phenomenon. Therefore, the influence of El Nino phenomenon on wetland vegetation is more than that of La Nina phenomenon, which is the possible reason for the decline of wetland vegetation NDVI after the turning point.

El Nino and La Nina have opposite effects on climate. El Nino will disturb the consistent climate characteristics of the region, that is, the precipitation in rainy season (or region) will decrease obviously, and the temperature in low temperature season (or region) will increase abnormally. La Nina, on the other hand, will significantly enhance the climate characteristics of the region, that is, the humid land will be wetter and the arid land will be drier (Luo, 2000). El Nino's disturbance of the original normal climate characteristics is the possible reason for the decline of wetland vegetation NDVI. However, the arrival of La Nina will change abnormal climate caused by El Nino, which plays a roughly opposite role to El Nino (Luo, 2000). This may explain that La Nina makes wetland vegetation NDVI increase.

4.2 Differences in response of wetland vegetation and non-wetland vegetation to climate change

Changes in vegetation activities are related to climate change (Musau et al., 2017; Piao et al., 2010; Sun et al., 2015). In this context, many scholars have done a lot of research on the relationship between climate change and vegetation cover (He et al., 2017; Lü et al., 2015; Li et al., 2019; Piao et al., 2014; Zhang et al., 2016; Zhang et al., 2018b). By comparing their findings with our research, it can be found that the impacts of climate change on wetland vegetation and non-wetland vegetation are different (Table 3). The positive correlation (negative correlation) in Table 3 indicates that there is a positive correlation (negative correlation) between indicators, but it has not passed the Two-tailed T test as a whole. The significantly positive correlation (negative correlation) indicates that the indicators have positive correlation (negative correlation) and pass the significance test.

In WA and S-WA, wetland vegetation is negative correlated with precipitation according to our data analysis. While other scholars have shown that non-wetland vegetation has positive correlation with temperature in WA of NS and CS, S-WA of WT and PT, WA and S-WA of MT (A et al., 2017; Chu et al., 2019; Gao et al., 2019; Liu et al., 2017; Xu et al., 2014). In S-AA and AA, wetland vegetation is positive correlated with precipitation, while non-wetland vegetation is significantly positive correlated with precipitation in general (Chen et al., 2016; Du et al., 2015b; Gao et al., 2019; Guli-Jiapaer et al., 2015; Li et al., 2018; Liu et al., 2017; Peng et al., 2011; Yang et al., 2016; Yang et al., 2018). In areas with sufficient water, non-wetland vegetation is more susceptible to temperature than wetland vegetation, while in areas with deficient water, non-wetland vegetation is more susceptible to precipitation than wetland vegetation.

In WT, non-wetland vegetation is significantly negative correlated with temperature in general (Wang, 2018), while wetland vegetation is positive correlated with temperature. In PT, non-wetland vegetation is significantly positive correlated with both temperature and precipitation in general (Guo et al., 2017; Li et al., 2018), while wetland vegetation is positive correlated with temperature. In areas with high temperatures, non-wetland vegetation is more susceptible to temperature than wetland vegetation.

Overall, non-wetland vegetation responds more significantly to climate change than wetland vegetation. The main reason is that the underlying surface of wetland vegetation is saturated or water exists. On one hand, wetland vegetation is less limited by water conditions, so the impact of precipitation

change on wetland vegetation is relatively small. On the other hand, water has a large heat capacity, and the evaporation of water alleviates the influence of temperature fluctuation.

4.3 The complexity of wetland vegetation response to climate change

When regional precipitation cannot meet the requirements of wetland vegetation growth, the increase of precipitation plays a positive role. AA of MT, which locates in western Inner Mongolia Plateau has very dry climate. It is inland, so humid airflow that comes from ocean is difficult to reach. The same situation occurs in S-AA and AA of PT. The increase of wetland vegetation NDVI in these areas is likely to be affected by the increase of precipitation.

In dry climates, temperature rise will have a negative impact on wetland vegetation growth. In S-AA which locates in Hulunbuir Plain, west Liaohe Plain and eastern Inner Mongolia Plateau, the increase of precipitation is the promoting factor of vegetation growth. However, the increase in temperature will greatly enhance the transpiration of wetland vegetation and destroy the water balance. Therefore, in these areas, the negative impact of temperature increase is greater than the positive impact of increased precipitation is a possible reason for the downward trend of wetland vegetation NDVI. In S-AA which locates in alpine valley in southern Tibet, precipitation increased slightly in long-term sequence. Because of the limited climatic characteristics such as limited precipitation and large evaporation, the temperature increase plays a leading role in the decline of wetland vegetation coverage.

In humid climates, the increase of precipitation will inhibit the growth of wetland vegetation. Excessive moisture can cause damage to vegetation, because it causes hypoxia and inhibits aerobic respiration of vegetation. In S-WA that locates in Songliao Plain, Sanjiang Plain and its southern mountainous areas, the humidity is relatively high and the decline of wetland vegetation NDVI is likely to be affected by the increase of precipitation.

Some wetland vegetation changes are due to the influence of local climate and geomorphological environment characteristics. Batang County, Ganzi Tibetan Autonomous Prefecture, Sichuan Province which locates in S-WA of PT, the topography here is complex and the vertical difference of climate is obvious under the joint influence of plateau airflow and monsoon. In this region, the temperature rises rapidly in spring, and summer there is hot and dry. The maximum temperature in summer exceeds 35 °C. After fall, the hot and cold air alternates and the microclimate frequently occurs (Chen, 2016). The wetland vegetation NDVI in this area is significantly negative correlated with temperature. With the increase of temperature, NDVI shows a downward trend in the long-term sequence. Because the growth season studied in this paper is from May to September, mainly including the end of spring, the whole summer and the beginning of autumn, it is inferred that the temperature increase exacerbates the hot and dry climate characteristics, and the transpiration increases resulting in a decline in wetland vegetation NDVI.

On national scale, the main controlling factor of vegetation change is the comprehensive regulation of natural factors such as temperature and precipitation (Yu et al., 2014). However, for wetland vegetation that locates at landscape scale such as Zoige Plateau, human activities are important factors that cannot be ignored. In WA which locates in Lesser Khingan Mountains and Changbai Mountains, large-scale production activities such as peat extraction, drainage, damming and mining have led to a rapid decline in wetland area in recent years (Zhang et al., 2009). A large amount of swamps were transformed into pastures in Zoige Plateau, so human activities may be one of the key incentives for wetland vegetation degradation in this region (Han et al., 2011). In that situation, the change of wetland vegetation NDVI is related to the superposition of climate fluctuations and human activities.

Existing studies have shown that higher temperatures in the middle and high latitudes of Northern Hemisphere will increase vegetation growth activity(Nemani et al., 2003). In areas where precipitation can meet the requirement of wetland vegetation growth, the increase of temperature will promote the growth activity of vegetation, which may be the reason why 63% of wetland vegetation is in a better environment with the increase of temperature. However, in areas with dry climate and insufficient precipitation, vegetation growth activity is mainly limited by water factors (Du et al., 2015c). The increase of temperature will lead to the decrease of soil moisture, which will lead to a worse environment of wetland vegetation.

5. Conclusions

This article aimed at characterizing the change trend of wetland vegetation in long time series and the differences in the response of wetland vegetation and non-wetland vegetation to climate change.

NDVI of wetland vegetation in China shows a significant change trend in 1981-2015 overall. Among them, 75% of NDVI change trend has turning point (concentrated in 2003 and 2004). Within the scope of this study, about 80% of the wetland vegetation NDVI shows a downward trend after the year of 2004, and about 10% of the wetland vegetation NDVI shows an upward trend after the year of 2003.

The environmental condition of wetland vegetation has changed significantly in 1981-2015. 63% of the wetland vegetation environment is in a gradually improving state, while 23% of the wetland vegetation environment is in a worse state.

The response of wetland vegetation NDVI to climate change is significantly different in space. Wetland vegetation NDVI is negative correlated with precipitation in humid areas, while it is positive correlated with precipitation in dry areas. In temperature-limited zones, wetland vegetation NDVI is positive correlated with temperature.

Extreme weather events such as El Nino and La Nina may affect wetland vegetation NDVI. La Nina phenomenon has a greater impact than El Nino phenomenon, which may be the reason why NDVI of wetland vegetation shows an upward trend before the turning point, while the impact of El Nino phenomenon is greater than La Nina phenomenon, which may be the reason why NDVI shows a downward trend after the turning point.

The response of wetland vegetation and non-wetland vegetation to climate change is significantly different, and the response of non-wetland vegetation to climate change is more significant. Compared with wetland vegetation, non-wetland vegetation is more likely to respond to changes in precipitation in arid regions and more susceptible to temperature changes in warmer areas.

The research scope of this paper covers 35 climate zones across China. Due to the fragmentation of wetland patches and the limitation of spatial resolution of data sources, no suitable wetland vegetation samples were selected in some areas. When discussing the difference in the response of wetland vegetation and non-wetland vegetation to climate change, a large number of literatures were searched, which still did not cover all wetland vegetation sample areas.

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Authors' Contributions XY wrote the manuscript and revised the paper. ZN conceived and designed the study, and RW implemented the experiment. The experimental results were co-analyzed by three authors. All authors read and approved the final manuscript.

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Data Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Code Availability The code generated to analyze datasets during this current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare no competing interests.

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588

590 **Table S1. The climatic zones where wetland vegetation samples are located**

Temperature Zone	Dry-Wet Zone	Climate Zone	ID
CT	WA	WA of CT of northern Da Hinggan Mountains	1-5
MT	WA	WA of MT of Xiao Hinggan Mountains and Changbai Mountain	6-11
	S-WA	S-WA of MT of Sanjiang Plain and its southern mountains	12-14
		S-WA of MT of Songliao Plain	15-17
		S-WA of MT of Central Da Hinggan Mountains	18-21
	S-AA	S-AA of MT of West Liaohe Plain	22-24
		S-AA of MT of Southern Da Hinggan Mountains	25-26
		S-AA of MT of Hulunbeier Plain	27-30
		S-AA of MT of Eastern Inner Mongolia Plateau	31-35
		S-AA of MT of Erdos and Donghetao	36-38
		S-AA of MT of Tacheng Basin	39-40
		S-AA of MT of Yili Valley	41-42
	AA	AA of MT of Xihetao and western Inner Mongolia Plateau	43-45
		AA of MT of Alashan and Hexi Corridor	46-49
		AA of MT of Junggar Basin	50-53
		AA of MT of Irtysh Valley	54-56
		AA of MT of Tianshan Mountain	57-59
WT	WA	WA of WT of low mountain hills in Liaodong	60
	S-WA	S-WA of WT of Yanshan Mountain	61
		S-WA of WT of North China Plain and Middle East Shandong Mountains	62
	AA	AA of WT of Tarim and East Xinjiang Basin	63-65
NS	WA	WA of NS of Dabie Mountain and North Jiangsu Plain	66
		WA of NS of Middle and Lower Reaches of the Yangtze River Plain and Northern Zhejiang	67
CS	WA	WA of CS of Jiangnan mountain area	68
PS-f	WA	WA of PS-f of Zoige Plateau	69-70
	S-WA	S-WA of PS-f of Golognaqu Alpine Valley	71-77
	S-AA	S-AA of PS-f of Southern Qinghai Plateau	78-83
		S-AA of PS-f of Qiangtang Plateau Lake Basin	84-88
	AA	AA of PS-f of Kunlun mountain	89
PT	WA	WA of PT of East and South Hengduan Mountains	90
	S-WA	S-WA of PT of North-central Hengduan Mountains	91-96
	S-AA	S-AA of PT of Qilian Qingdong Alpine Basin	97-102
		S-AA of PT of Alpine Valley in South Tibet	103-108
	AA	AA of PT of Qaidam Basin and North Wing of Kunlun Mountains	109-114
		AA of PT of Ali Mountain	115-117

Tables

Table 1 The percentage of samples with different NDVI value in each wet-dry zone (unite: %)

	NDVI $\geq$ 0.6	0.3 < NDVI < 0.6	NDVI $\leq$ 0.3
WA	44	4	0
S-WA	38	24	0
S-AA	12	57	41
AA	6	15	59

Note: WA is Wet Area; S-WA is Semi-Wet Area; S-AA is Semi-Arid Area; AA is Arid Area.

Table 2 The percentage of samples with partial correlation between SWeV NDVI and climate indicators in each climate zone (unite: %)

	TP exists								TP doesn't exist			
	Before TP				After TP							
	PCorr_NDVI&T		PCorr_NDVI&P		PCorr_NDVI&T		PCorr_NDVI&P		PCorr_NDVI&T		PCorr_NDVI&P	
	+	-	+	-	+	-	+	-	+	-	+	-
WA	71	29	21	79	57	43	14	86				
S-WA	50	50	45	55	75	25	35	65	67	33	0	100
S-AA	57	43	77	23	57	43	63	37	33	67	67	33
AA	68	32	79	21	68	32	63	37	89	11	67	33
CT	75	25	25	75	75	25	0	100				
MT	50	50	67	33	60	40	48	52	67	33	67	33
WT	67	33	100	0	33	67	100	0				
PT	46	54	46	54	62	38	54	46	77	23	69	31
PS-f	92	8	62	38	85	15	54	46	14	86	43	57

Note: “PCorr_NDVI&T” is the partial correlation between NDVI and Temperature; “PCorr_NDVI&P” is the partial correlation between NDVI and precipitation. TP is turning point; WA is Wet Area; S-WA is Semi-Wet Area; S-AA is Semi-Arid Area; AA is Arid Area; CT is Cold temperature zone; MT is Medium temperature zone; WT is Warm temperate zone; PS-f is Plateau sub-frigid zone; PT is Plateau temperate zone.

“+” represents positive correlation; “-” represents negative correlation.

Table 3 Response of wetland vegetation and non-wetland vegetation to climate change in different climate zones and dry-wet zones

	WA		S-WA		S-AA		AA	
	GV	WV	GV	WV	GV	WV	GV	WV
	T	P	T	P	T	P	T	P
CT			+	-				
MT	x	-**	-	-	-	-	+(3)	-
WT			+	+	-	x	-	+
NS	+(2)		x	-			-**	+(2)

CS	+	X	+	-														
PS-f			X	X		+	+	X	***	-	-					+	+	
PT			-	-	+	X	+	-	***	+	-	+	***	***	+	X		

Figure captions

Figures

Figure 1

The temporal trajectory variations of NDVI of SWeV sample from 1981 to 2015

Figure 2

The distribution of SWeV samples in wet-dry zones and temperature zones

Figure 3

The average value and variance of NDVI of wetland vegetation samples in wet-dry zones (a) and temperature zones (b). (WA is Wet Area; S-WA is Semi-Wet Area; S-AA is Semi-Arid Area; AA is Arid Area).

CT is Cold Temperature Zone; MT is Medium Temperature Zone; WT is Warm Temperate Zone; NS is North Subtropical; CS is Central Subtropical; PS-f is Plateau Sub-frigid Zone; PT is Plateau Temperate Zone.)

Figure 4

The years in which the turning point (TP) is located (a) and spatial change trends of NDVI (b) of 117 SWeV samples

Figure 5

Spatial change trends of VCI of 117 SWeV samples

Figure 6

Spatio-temporal change trends of near-surface temperature (a) and ground precipitation rate (b)

Figure 7

One example of inter-annual variation trend of SWeV NDVI corresponds to El Nino and La Nina years