Variance of vegetation coverage and its sensitivity to climatic factors in Irtysh River basin (#55104)

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Variance of vegetation coverage and its sensitivity to climatic factors in Irtysh River basin

Feifei Han [1], **Junjie Yan** [Corresp., 2, 3], **Hong-bo Ling** [Corresp. 2]

[1] College of Water and Architectural Engineering, Shihezi university, Shihezi, China

[2] State Key Laboratory of Desert and Oasis Ecology, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences (CAS), Urumqi, China

[3] Institute of resources and ecology, Yili Normal University, Yining, China

Corresponding Authors: Junjie Yan, Hong-bo Ling
Email address: yan3550@sina.com, linghb@ms.xjb.ac.cn

Background. Climate change is an important factor driving vegetation changes in arid areas. Identifying the sensitivity of vegetation to climate variability is crucial for developing sustainable ecosystem management strategies. Irtysh River is located in the westerly partition of China, and its vegetation cover is more sensitive to climate change. However, previous studies rarely studied the changes in the vegetation coverage of the Irtysh River and its sensitivity to climate factors from a spatiotemporal perspective.

Methods. we adopted a vegetation sensitivity index (VSI) based on high-resolution remote sensing datasets to study the sensitivity of vegetation to climatic factors in Irtysh River basin, then reveal the driving mechanism of vegetation cover change.

Results. The results show that 88.09% of vegetated pixels show an increasing trend in vegetation coverage, and the sensitivity of vegetation to climate change presents spatial heterogeneity. Sensitivity of vegetation increases with the increase of coverage. Temperate steppe in the northern mountain and herbaceous swamp and broadleaf forest in the river valley, where the NDVI is the highest, show the strongest sensitivity, while the desert steppe in the northern plain, where the NDVI is the lowest, shows the strongest memory effect (or the strongest resilience). Relatively, the northern part of this area is more affected by a combination of precipitation and temperature, while the southern plains dominated by desert steppe are more sensitive to precipitation. Central river valley dominated by herbaceous swamp is more sensitive to TVDI. This study underscores that the sensitivity of vegetation cover to climate change is spatially differentiated at the regional scale.

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Feifei Han[1], Junjie Yan[2,3], Hongbo Ling[2]

[1] College of Water and Architectural Engineering, Shihezi university, Shihezi, Xinjiang, China
[2] State Key Laboratory of Desert and Oasis Ecology, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences (CAS), Urumqi, Xinjiang, China
[3] Institute of resources and ecology, Yili Normal University, Yining, Xinjiang, China

Corresponding Author:
Junjie Yan[2,3], Hongbo Ling[2]
No. 818 South Beijing Road, Urumqi, Xinjiang, 830011, China
Email address: yan3550@sina.com (J. Yan); linghb@ms.xjb.ac.cn (H. Ling).

Abstract

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Introduction

Vegetation covers nearly three-quarters of the land surface(Sarkar and Kafatos, 2004), which is the main body of the terrestrial ecosystem(Cramer and Leemans, 1993), and plays an important role in linking the soil and atmosphere through energy and mass transport(Deng et al., 2017). In the context of global climate change, on the one hand, vegetation is affected by climate change and becomes the sufferers of climate change. Besides, it acts as an "indicator" in global climate change research(Piao et al., 2006). On the other hand, vegetation is related to climate characteristics, and its change has a positive feedback effect on climate change (Liu et al., 2006; Sun et al., 2018). Therefore, monitoring and mapping the sensitivity of vegetation to current climate variability is crucial for projecting future vegetation dynamics and developing sustainable ecosystem management strategies.

Investigating the responses of vegetation to short-term climate anomalies is of great significance to mitigate the ecological, economic, and social consequences of future climate change (Huete and Alfredo, 2016). Much current understanding of vegetation's respond to climate change is based on changes in mean climate state (Mearns et al., 1997; Thomas et al., 2004). We consider that this mean state can only represent changes in the equilibrium state (e.g. due to overgrazing or long-term successional cycles (Clifford et al., 2011)) instead of anomalies resulting from short-term climate anomalies. However, the response of vegetation to changing climate is comprehensive and often varies dramatically between regions(Anav and Mariotti, 2011). Given the importance of identifying ecologically sensitive areas for ecosystem service provision (Egoh et al., 2020), a key knowledge gap exists in how to identify and then prioritize those regions that are more sensitive to climatic variability. However, a key issue must be addressed before we analyze the sensitivity of vegetation to climate variability, that is, how to describe vegetation sensitivity in a quantitative way. There are several ways defining the vegetation's sensitivity to climate variability. For example, vegetation's sensitivity refers to the degree and magnitude of vegetation response when the climate anomaly occurs(You et al., 2018) or the degree to which a system changes after a disturbance(Li et al., 2018). In this study, vegetation's sensitivity is defined as the magnitude of vegetation response at the moment of the climate anomaly(Tilman, 1996). Additionally, Moulin S et al. (Moulin et al., 1997) found that due to the relatively slow growth of vegetation, the response of vegetation to climate change often lags, in that its state depends both on current disturbances and the residual effects of past climate conditions. This 'memory effect' should be considered when assessing the immediate response to short-term climate anomalies(De Keersmaecker et al., 2015). In this study, we describe memory effects as the amount of time required to resume the normal after stress (Lhermitte et al.,

2010), or the persistence of trends in temporal changes of ecosystem properties(Dash et al., 2014; Simoniello et al., 2008).

Since the 1970s, the development of satellite remote sensing technology has made it possible for a human to conduct macro dynamic monitoring of earth vegetation from space (Pettorelli et al., 2014; Weng, 2002). In the past decades, there has been an increase in the availability of satellite data measuring climate and other ecologically relevant variables(Kerr and Ostrovsky, 2003). These data offer opportunities to characterize ecosystem sensitivity at high spatial resolution. Among various methods, Seddon et al. (Seddon et al., 2016) present a novel method to identify ecosystem sensitivity and memory effect to short-term climate variability by developing a vegetation sensitivity index (VSI) that explores the linkage between variability in vegetation productivity (defined as EVI) and three climate variables (namely air temperature, water availability, and cloud-cover) on monthly time scales. The vegetation sensitivity index is a useful metric to quantitatively assess the sensitivity of different ecosystems to climate variability (Huete, 2016; Willis et al., 2018) and simultaneously takes into account metrics standardizing for short-term climate effects and vegetation 'memory'. Therefore, we apply this method to identify the sensitivity of vegetation to climate variability and reveal the potential influence of memory effects. Temperature and precipitation are usually the main climatic factors affecting vegetation activities (Li et al., 2015; Seddon et al., 2016; Yang et al., 2015). Supply of water, quantified with moisture of the soil, is also a profound factor affecting vegetation activities in the arid area. And the temperature-vegetation dryness index (TVDI) originated from remote sensing data can reflect the variation in soil moisture on a finer scale(Grassini et al., 2010; Sandholt et al., 2002). So, we substitute the climatic factors in their model by temperature, precipitation, and TVDI. Additionally, as the normalized difference vegetation index (NDVI) can well reflect the vegetation chlorophyll content, leaf area, leaf biomass, net productivity, coverage and other surface vegetation coverage information (Bounoua et al., 2000; Goetz et al., 1999; Tieszen et al., 1997), and is most widely used in many vegetation indexes (Defries and Townshend, 1994; Myneni et al., 1997; Paruelo et al., 1997). Therefore, we chose NDVI instead of EVI to characterize vegetation coverage.

Drylands (including arid and semi-arid regions) occupy over 41% of the global land surface area and are inhabited by >2 billion people (Safriel et al., 2020). Ecosystems in arid and semi-arid regions are more vulnerable to climatic disturbances(Rotenberg and Yakir, 2010). Irtysh River basin is located in the arid and semi-arid region in the northwest of China where water resources are scarce, and it is an important water source in this area and plays an important role in regional economic development and ecological protection(Ye and Bai, 2014). At the same time,

the Irtysh River is an international river, which has complicated interests with neighboring countries in the international distribution of water resources, prevention and control of water pollution, ecological maintenance and international regional cooperation. On this basis, this study selected Irtysh River basin, which is sensitive to environmental change, as the study area, analyzes its vegetation change and climate change characteristics, and identifies the area sensitive to climate change, which has important reference significance for the future how to deal with climate change and ecological civilization construction of the basin.

Based on the remote sensing data, we used the Mann-Kendall non-parametric rank statistical test to analyze the vegetation dynamic and then calculated VSI to discuss the vegetation sensitivity. In this study, our aims are to (1) map the spatial trends of vegetation cover in 2000-2018; (2) investigate the controlling factors of vegetation sensitivity and resilience in Irtysh River basin.

Materials & Methods

Study area

Irtysh River basin is in the arid and semi-arid area of northwest China where water resources are scare (45° 40′ ~48° 27′ N, 85° 30′ ~91° 2′ E, Fig.1). The region relates to the Altai Mountains in the north and crosses into the northern edge of the fold system of the Junggar Basin in the south and is adjacent to Mongolia, Kazakhstan, and other countries in the East and West. A typical temperate continent cold climate(Ju et al., 2015; QiangJi and Wu, 2017) dominates this area, with annual mean temperature ranging from 3.6℃ to 3.9℃, and the cold air activities are frequent in winter and spring in mountainous areas, forming disasters such as blizzards, snowstorms, and avalanches now and then. The annual mean precipitation is about 217.1 mm, the precipitation increases gradually alone the increase of elevation, yet the northwest part is wetter than the southeast part in general(Shen et al., 2007). The vegetation in the study area is mainly desert meadow and grassland, accounting for 91.58% of the whole vegetated area. The rest are herbaceous swamp distributed in and around the river valley, and broad-leaved forest or shrub scattered in or near the swamp area.

Data source and pre-processing

Meteorological Data

This study collected monthly precipitation and air temperature datasets covering the period of 2000–2018 from the China Meteorological Data Service Center (CMDC). Data of 72 meteorological stations in the territory of

Xinjiang province of China, where the study area located, were utilized to interpolate continuous surfaces data using the Anusplin4.2 interpolation program. The spatial resolution was set to 250 m in the interpolating. Among the 72 meteorological stations, 7 are in the study area (Fig.1).

Remote sensing Data

Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI product (MOD13Q1) covering the period of 2000-2018 were used to determine the variation of vegetation cover. This MOD13Q1 product was 16-day NDVI synthetic data using the Maximum Value Composite (MVC) method, and its pix size is about 250 m×250 m. We performed Savitzky-Golay filtering on the NDVI time series to obtain high-quality data, then MVC were applied to get monthly and yearly NDVI.

Temperature Vegetation Dryness Index (TVDI) can be used to characterize the degree of soil drought. This study mainly uses the method proposed by Sanholt I et al. and Yao et al. (Sandholt et al., 2002; Yao et al., 2004) to calculate TVDI. TVDI is a combination of vegetation index (VI) and land surface temperature (LST). Monthly TVDI were calculated using the MODIS NDVI and the 8-day composite MODIS temperature product (MOD11A2). The MOD11A2 product includes LST images of day and night, with a pix size about 1000 m×1000 m. The day LST was used in the study. Every 4 LST images covering the whole corresponding month were averaged to get the monthly LST time series data, and the pix size was resampled to 250 m×250 m to match the images of NDVI.

It is well known that there are ubiquitous data gaps in LST datasets because of non-overlapping satellite orbits, cloud contamination, instrumental malfunction (Chen et al., 2011; Hu et al., 2014). In this study, we applied a penalized least square method based on discrete cosine transforms (DCT-PLS) to fill data gaps in MODIS LST datasets(Liu et al., 2020), this method has been proved fast and robust to fill LST datasets.

Mann-Kendall non-parametric rank statistical test

When using Mann-Kendall non-parametric test(Kendall, 1990; Mann, 1945) to test the possible trends of climatic elements and time series, we assume that H0 indicates that the time series （x1,x2 ,…, xn） are independent of the data sample, and there is no obvious trend; Assuming that H1 is a bilateral test, the distribution of xi and xj are different for all i, j (i≠j), the calculation formula of the statistical variable S of the test is as follows:

$$S = \sum_{i=1}^{n-1} \sum_{k=i+1}^{n} Sgn(x_k - x_i) \quad (1)$$

Among them,

153 $$Sgn\ ((\theta)) = \begin{cases} 1 & \theta > 0 \\ 0 & \theta = 0 \\ -1 & \theta < 0 \end{cases}$$

154 （2）

155 S is normal distribution, the mean is 0, and the variance is as follows:

156 $$Var(s) = \left[n(n-1)(2n+5) - \sum_t t(t-1)(2t+5)\right]/18 \quad (3)$$

157 Where t is the width of each unit. When n> 10, Zc converges to a standard normal distribution and can be

158 calculated by the following formula.

159 $$Z_c = \begin{cases} \dfrac{S-1}{\sqrt{Var(S)}} & S > 0 \\ 0 & S = 0 \\ \dfrac{S+1}{\sqrt{Var(S)}} & S < 0 \end{cases} \quad (4)$$

160 At a given α confidence level, when |Zc|>1.96, the changing trend reaches a significant level, |Zc|<1.96, the

161 changing trend is not Significant; Zc>0, indicating that the changing trend is increasing, and Zc<0, it is decreasing.

162 Among them, the size of the changing trend can be expressed by Kendall slope, and its calculation formula is as

163 follows:

164 $$\beta = Median\left(\frac{x_i - x_j}{i-j}\right) \quad (5)$$

165 In the formula, 1<j<i<n，β means slope, a positive value means “uptrend”, and a negative value means

166 “downtrend”.

167 **Identifying the sensitivity of vegetation to climate variability**

168 The VSI is a novel and empirical metric developed by Seddon et al. (2016) that can quantify the sensitivity of

169 different vegetation areas to climate variability (Huete, 2016; Willis et al., 2018). In this study, we tailored the

170 empirical methodology to identify vegetation sensitive to climate variability on the Irtysh River basin.

171 Firstly, for the climatic variables, we employed temperature, precipitation, and TVDI, instead of three climate

172 variables as in Seddon et al. (2016). Furthermore, we included the one-month-lagged NDVI monthly data as a fourth

173 variable in the regression to investigate the potential influence of memory effects driving vegetation dynamics.

174 Secondly, any month with a mean NDVI of <0.1 were excluded to reduce the potential impact of noisy data at

175 low NDVI values, which are attributed to areas with extremely sparse or inexistent vegetation cover. And to remove

seasonal component underlying monthly time series, we de-trended the monthly data and then we standardized the de-trended data utilizing the Z-score standardization formula:

$$Z_{i,j} = \frac{x_{i,j} - \bar{x}_j}{\sigma_j} \quad (6)$$

Where xi,j is the detrended data in the jth month of the ith year, xj and $\sigma_j$are the mean and standard deviation of the variable x in the jth month of all years, respectively.

Thirdly, in this study, the sensitivity of vegetation to climate variability on the Irtysh River basin was primarily calculated using AR1 multiple linear regression approach in each pixel, as follows:

$$NDVI_t = \alpha \times NDVI_{t-1} + \beta \times Tem_t + \gamma \times Pre_t + \delta \times TVDI_t + \varepsilon_t \quad (7)$$

Where $NDVI_t$ is the standardized NDVI at time t, $NDVI_{t-1}$ is the standardized NDVI anomaly at time t-1,Tem_t, Pre_t and $TVDI_t$ are the standardized temperature, precipitation, and TVDI at time t, respectively. ε_t is the residual term at time t, and $\alpha, \beta, \gamma, and\ \delta$ are coefficients for temperature, precipitation, TVDI and $NDVI_{t-1}$ of each pixel, respectively. Each of $\alpha, \beta, \gamma, and\ \delta$ is a metric of ecosystem stability (Table 1; (De Keersmaecker et al., 2015)). Compared to the correlation coefficient which can only indicate whether the ecosystem responds to climate variability, the regressive coefficient can further reflect the response magnitude.

Fourthly, to eliminate the effects of co-linearity between four climate variables, the principal components regression (PCR) was also applied within each pixel to quantify the relative importance of each variable driving variations in the monthly NDVI (Seddon et al., 2016). The principal components that had significant relationships with climate ($p < 0.1$) were selected, and we subsequently multiplied the loading scores of each variable by the PCR coefficients. The product scores were summed to estimate the relative importance of each variable in driving monthly changes in NDVI, which provided an empirical approach for mapping the relative importance of climate on vegetation change (climate weights).

The climate weights from each variable were rescaled between 0 and 1 (using the minimum and maximum values of any of the climate coefficient values), to be used for calculations of vegetation sensitivity. To estimate the variations of both the climate variables and NDVI on these time series, we used the residuals of a linear model fitted to the mean-variance. Relationship of both the NDVI and climate variables for each pixel. We standardized these residuals to between 0 and 100 for each variable. Our sensitivity metrics are the log10-transformed ratios of NDVI

variability and each of the climate variables. Each ratio was then weighted according to the importance of the climate variable to EVI variability by multiplying it by the value of the regression coefficient (climate weights).

Finally, we summed the sensitivity scores for each of our variables to identify areas of enhanced variability for the period of study.

$$VSI = Tem_{wei} \times Tem_{sens} + Pre_{wei} \times Pre_{sens} + TVDI_{wei} \times TVDI_{sens} \quad (8)$$

The VSI has no units and therefore provides relative information, wherein a high VSI value is associated with a high response rate of vegetation productivity to climate variability. The detailed algorithm for calculating VSI and the R script can be found in Seddon et al. (2016).

Results

Variances in vegetation cover and climatic factors

Based on the annual NDVI data of the study area in 2000-2018, we calculated the annually mean NDVI on a pixel scale and divided it into 5 levels (Fig.2a) to analyze its spatial pattern. Vegetation coverage in the study area increased from the southern plain to the northern mountain area. Vegetation in the plain area, except for the river valley, had low coverage (NDVI<0.2) and occupied 68.03% of the vegetated pixels. NDVI of the mountain areas in the north and some plain areas in the west is about 0.2-0.6, accounting for 24.08% of the vegetated pixels. The central valley area, which is where the wetland and broad-leaved forest distribute, showed high coverage (NDVI>0.6), accounting for 7.89% of the vegetated pixels.

In the period of 2000-2018, the annually averaged NDVI of the whole study area shows a significant increase trend (statistics Zc=2.17, P<0.05), the changing rate β is 0.0017 (Fig.3). Spatially, the NDVI of 70.28% of the vegetated pixels showed non-significant increase trend and they are mainly located in the low coverage region dominated by desert meadow and grassland (Fig.2b). 17.81% of the vegetated pixels showed a significant increasing trend, and are mainly located in the western part and central part in the south. Areas with NDVI showing decreasing trend are sparsely distributed in the northern piedmont area and part of the west end. For the changing rate β，the proportion of pixels with β>0 reached 89.04%. NDVI of areas in the central valley, mountains in the east and central plains of the south showed the most rapid increase(β>0.002), the proportion is 26.79%.The increasing rate was relatively low(0<β<0.001) for the plain of the east and southwest, and the central mountain of the south, which occupied 62.26% of the vegetated pixels.

Climatic factors are the main driving forces for variation of vegetation. Therefor we performed Mann-Kendall tests on precipitation, temperature and TVDI data to reveal their changing trends separately. The results (Fig.4) showed that the precipitation and temperature in the study area showed a non-significant increasing trend from 2000 to 2018, meaning whether condition in the study area were getting warmer and wetter. Relatively, TVDI in the study area showed a non-significant decreasing trend from 2000 to 2018, indicating that the soil moisture in the study area is gradually increasing. The increased precipitation and temperature and decreased TVDI indicate that the hydrothermal conditions and soils required for vegetation growth in the study area have been greatly improved in the past 19 years, which promoted the increasing of the NDVI for the whole study area.

Vegetation Memory effects

Vegetation memory effects have been widely reported in water-limited ecosystems at various time-scales (Los et al., 2006; Schwinning et al., 2004). Seddon et al. found that a one-month lag provided the best explanatory power for vegetation responses to variability on short-term timescales. Therefore, we included the one-month-lagged NDVI monthly data as a fourth variable in the regression to investigate the potential influence of memory effects driving vegetation dynamics. The areas with high variance explained by the t−1 variable in the AR1 model, indicating systems where memory effects play a more important role than contemporary climate conditions in determining vegetation cover (Fig.5). The larger the t-1 coefficient weight (that is, coefficient α), the stronger the memory effect, and the weaker the sensitivity (with lower VSI).

Vegetation showed strong memory effects ($\alpha>0.4$) across almost the whole study area (Fig.5), especially in some parts of the eastern plain where the coefficient reached more than 0.6, and the area with $\alpha>0.6$ accounted for 27.27% of the vegetated pixels in the study area. Coefficient α of areas in the northwest, the border of the east and river valley in the middle is relatively small ($\alpha<0.4$), indicating weaker memory effects, and the areas proportion is 20.60%. Yet for most parts of the study area, the coefficient α is about 0.4-0.6, and the area proportion reached 52.13%. Notably, vegetation with big NDVI showed weak memory effect in general, such as the herbaceous swamp and broadleaf forest in the river valley and grassland in the mountain area of the north border. In contrast, the desert grass in the plain area showed strong memory effect.

As shown in Fig.6, the memory effect tends to change along the gradient of NDVI and climatic factors. To identify the controlling factors for vegetation memory effects, we regressed α (t-1 coefficient weight) against three climatic factors (precipitation, temperature, and TVDI) and vegetation cover (defined as NDVI). And considering the hydrothermal conditions required for vegetation growth, we selected the mean NDVI, mean precipitation, mean

temperature, and mean TVDI of the growing season (GS) to participate in the regression. The results showed that vegetation memory effects (α) decreased logarithmically as NDVI increased (R^2=0.67, $P<0.05$, Fig.6a). Relatively, vegetation memory effects (α) increased logarithmically as TVDI increased (R^2=0.407, $P<0.05$, Fig.6d). Specifically, vegetation memory effects (α) presented a quadratic parabola relationship with both precipitation (R^2=0.202, $P<0.05$, Fig.6b) and temperature (R^2=0.155, $P<0.05$, Fig.6c).

Vegetation sensitivity to climatic variables

Compared to strong memory effects, the VSI in the study area is rather low, with 60.69% of the vegetated pixels where VSI is less than 30 (Fig.7b). Spatially, areas of big VSI (VSI>30) generally overlap that of weak memory effects (α<0.4), such as the grassland in the north border and herbaceous swamp and broadleaf forest in the river valley, indicating that areas with higher NDVI usually shows weaker memory effects and higher sensitivity to climate variability over the past 19 years. Areas of the desert plain show low sensitivity (VSI>30) to climate variability, and overlap the areas of strong memory effects (α>0.4).

The relative importance of three climate variables (temperature, precipitation, and TVDI) to vegetation sensitivity also displayed clear spatially heterogeneity across the study area (Fig.8). Most areas are more sensitive to precipitation, mainly distributed in the southern and central plains dominated by desert meadow. While variation in vegetation cover (defined as NDVI) of the southeastern areas were mainly affected by a combination of precipitation and temperature, and the northern part of this area is affected by a combination of TVDI and temperature. Additionally, vegetation cover in the northwest areas was mainly driven by precipitation and TVDI. Remarkably, the central river valley dominated by herbaceous swamp was more sensitive to TVDI. And the mountain areas with higher elevations in the north are more sensitive to both temperature and precipitation.

Discussion

Disentangling the driving factors for variations in vegetation cover

Irtysh River basin is located in arid and semi-arid region. Scarce precipitation and high temperature lead to large evapotranspiration and low soil water storage in this area, which is not conducive to the growth of vegetation, especially in the low land of the southern plain. Therefore, most part of the study area is dominated by desert vegetation. However, as the altitude increases, the precipitation increases and temperature decreases (Navarro et al., 2020), and this relieves the severe climatic restrictions. So, grassland in areas of high altitude, mainly the mountain areas in the north, is well developed and the vegetation coverage is also high (0.4<NDVI<0.6). The river valley can

rely on the rivers to supply ample water required for vegetation growth, so the herbaceous swamp and broadleaf forest with the highest NDVI (NDVI>0.6) are well developed in this area.

The results of the Mann-Kendall trend test of climatic factors show that the temperature and precipitation in the study area showed an increasing trend from 2000 to 2018, and the TVDI showed a decreasing trend. This is consistent with the findings of Huang et al (Huang et al., 2013). The analysis of the results indicate that the hydrothermal and soil conditions required for vegetation growth in the Irtysh River basin have been greatly improved. However, with the change of altitude gradient and climatic factors, the variation trend (Zc) and rate (β) of vegetation cover show obvious spatial heterogeneity. The increase of rainfall brings abundant water resources to the desert plain area in the southern study area, improves the available moisture content of the local soil, thus promoting the absorption of plant nutrients, which is conducive to the improvement of water utilization rate of plants, and greatly promotes the growth of vegetation and the increasing rate of local vegetation cover. The vegetation growth in the central valley, which is dominated by herbaceous marshes, mainly depends on rivers to supply groundwater to meet the requirements of soil moisture. In recent years, with the continuous strengthening of national ecological protection, the ecological water volume of Irtysh River has been well guaranteed (Yang et al., 2012; Ye and Bai, 2014), which can timely recharge the groundwater aquifer in the valley area, thus increasing the soil moisture in this area, and TVDI presents a decreasing trend. In addition to the supply of rainfall, the vegetation cover in this region showed a significant trend of increase from 2000 to 2018, and the increase rate was also very fast. Studies (Jiang et al., 2017) have shown that the impact of air temperature on vegetation growth is topographically different. In the central river valley where it is relatively wet, elevated temperature can promote plant photosynthetic activity and thus lead to a positive response of vegetation growth. In the northern study region where it is relatively dry, increase of temperature can intensify the water deficit through elevated evaporation and thus causes a negative response of NDVI. In particular, although the climatic conditions in the study area showed a pattern of improvement, the impact of human activities on vegetation cover could not be ignored. The research results of Yang et al.(Han et al., 2013) showed that from 1990 to 2010, the overall landscape pattern of the Irtysh River Basin tended to be fragmented, with serious spatial heterogeneity, which was increasingly affected by human activities over time. The research results of this paper also reflect this phenomenon. The regions with different elevations have different responses to the same climatic factors.

Environmental impacts on vegetation memory effect during growth season

We can see in Fig.5 that areas with the strongest memory effects are generally located in the desert pain of the southeast, where the NDVI is the smallest and the drought the strongest. And areas with weakest memory effects is gathered in the mountain areas of the north and river valleys in the middle, where the NDVI is the biggest and the drought the weakest. This character in the matching between the memory effects and both of NDVI and drought can also be seen in the clean decreasing trend of metric α along with the increasing NDVI and also the increasing trend with the increasing TVDI (Fig.6a, 6d). Vegetation in the arid area or desert are usually characterized by their strong capability to coping with disturbances in climatic factors, this can be seen in the constant and largely stable low productivity conditions despite large climate variability and also strong cyclical variability with periods of very low and stable NDVI. So vegetation of these areas usually show strong memory effects. This contrasts to areas with high NDVI, such as the river valley and the mountain area, where the river water and the more precipitation can moderate the severe drought and provide better conditions for vegetation growth, yet the growth of vegetation is restricted by the variation in water supply.

In addition, vegetation memory effects in the study area does not show a clear linear relationship with temperature and precipitation, but we can see from the figure (Fig.6b, 6c) that there is an obvious inflection point in the image, which means there a threshold in both the precipitation and temperature effects on memory effects. This might be related to the co-effect of temperature and precipitation on vegetation. For areas in the arid region, altitude usually controls the spatial differentiation of precipitation and temperature, therefor relationship between the memory effects and climatic factors are branded with the influences of altitude on temperature and precipitation. Plain of low altitude is usually characterized by high temperature and scare precipitation, whereas mountain areas are usually characterized by low temperature and abundant precipitation. So, the limiting factor on the growth of vegetation changes gradually from precipitation to temperature along the variation in altitude, which results in vegetation changes in certain areas are co-affected of temperature and precipitation and the threshold in both the precipitation and temperature effects on memory effects.

Spatial heterogeneity of VSI distribution

VSI reflects the sensitivity of vegetation cover to climate change, and we can identify regions that exhibits amplified responses to climate variability through VSI. While Memory effect measures the capability of vegetation returning to its normal state after suffering the disturbance. Specially, areas with low VSI values showed the largest memory effect (Seddon et al., 2016), which is consistent with our study results（Fig.5 and Fig.7a）.The desert plain

area in the south of the study area has low sensitivity to climate change and strong vegetation memory effect. When the adverse conditions for vegetation growth are generated due to the vicious climate development or other disturbances in the region, the vegetation will make a hysteresis response to such changes, so that the ecosystem can make timely adjustments to the environmental deterioration. Different types of vegetation respond differently. The main vegetation type is desert meadow, which is a short-lived plant that survives in arid areas by escaping drought (Guo et al., 2004; Lu et al., 2019). The ephemeral plants germinate and grow quickly in spring when the elevated temperature melts the frozen soil or the covering snow and complete their life cycle before the coming of the hot and dry summer. In addition, studies (J.Z. and H.J., 2015) have shown that the water content of soil at different depths is affected differently by precipitation. Among them, the water content of shallow soil (0-20cm) is most affected by precipitation. Desert meadow in arid and semi-arid areas have relatively short rooting system that mainly absorb moisture from shallow soil, so the vegetation changes in this area are more sensitive to precipitation.

In contrast to the desert plain area in the south, the central Irtysh River valley showed higher sensitivity and weaker memory effect. The central river valley area is dominated by herbaceous swamps, which are typical low-level swamps, with year-round accumulation of water or drenched soil (H.Y. et al., 2020), and the water supply mainly depends on the Irtysh River. The local vegetation is dominated by perennial plants such as caress and gramineous plants. Many plants have short root systems and mainly absorb shallow soil water, which are highly dependent on soil moisture conditions. Therefore, when the amount of river water decreases, the soil water content of the swamp will also decrease, exerting a hard impact on the growth of herbs. Additionally，TVDI is an index reflecting soil moisture, smaller TVDI indicates that the wetter soil (Sandholt et al., 2002), so the vegetation on the site is more sensitive to TVDI.

It is worth noting that the northern mountain regions show strong sensitivity to climate change (VSI>50 in some areas). And the vegetation variation in this area is mainly affected by the combined effects of temperature and precipitation. Compared to the powerful ability of the desert plants in coping the severe drought, temperate steppe in the mountain area is well developed because the elevated altitude relieves both the restrictions of scarce precipitation and high temperature and provides hydrothermal conditions suitable for the grass plants, which makes variations in the coverage of temperate steppe are sensitive to both the precipitation and temperature.

Conclusions

This study applied a comprehensive new method to quantify the sensitivity and memory effects of vegetation in the Irtysh River basin to climate change based on high temporal and spatial resolution datasets, and further reveal the mechanism of vegetation response to climate change at the regional scale. What's more, we applied a fast and robust method (DCT-PLS) to fill data gaps in MODIS LST datasets in order to make the calculation results of TVDI more accurate. For the period of 2000-2018, the variation trend of precipitation, temperature and TVDI all showed that the climate condition of the Irtysh River basin had been greatly improved, and the vegetation coverage also showed overall increasing trend. From the south to the north of the study area, with the change of topographic and geomorphic features, the memory effect of vegetation and its sensitivity to different climatic factors showed obvious spatial heterogeneity. It is mainly manifested in the following aspects, the memory effect of vegetation in the southern desert plain was stronger and the plants there are more sensitive to precipitation, while the herbaceous swamp and broad-leaf forest in the central valley showed weaker memory effect and were more sensitive to TVDI. The temperate steppe in the northern mountain is highly sensitive to climate change and were more affected by the combination of both precipitation and temperature. Factors influencing the memory effect of vegetation were also analyzed. These results will help us locate different ecological protection environment types more accurately in the future basin management process, and develop optimal adaptive ecological protection strategies to protect this vulnerable ecosystem.

Acknowledgements

This work was supported by the Xinjiang Tianshan Youth Program (2019Q006)，West Light Foundation of Chinese Academy of Sciences (2019-XBQNXZ-A-001) and Science and Technology Service Network Project of Chinese Academy of Sciences (KFJ-STSQYZD-114).

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Table 1(on next page)

Interpretation of the coefficients in the AR1 multiple linear regression approach

Interpretation of the coefficients in the AR1 multiple linear regression approach

1 **Table 1**
2 Interpretation of the coefficients in the AR1 multiple linear regression approach

Coefficient	Implication	Meaning of absolute value	Meaning of sign
α	Revealing the potential influence of memory effects driving vegetation dynamics.	A large absolute value indicates low resilience, which means that vegetation slowly recovers from previous disturbance.	Positive value of δ shows NDVI is similar to the previous anomaly. Negative value of δ shows NDVI is similar to the previous anomaly but with the opposite trend.
$\beta/\gamma/\delta$	Climatic sensitivity index denoting the magnitude of immediate response of vegetation to the contemporary variation in climate variable.	Large absolute values indicate low resistance to temperature/precipitation/TVDI.	Positive Higher temperature/precipitation/TVDI than average induces a positive NDVI response (higher NDVI). Negative Lower temperature/precipitation/TVDI than average induces a negative NDVI response (lower NDVI).

3

Figure 1

Overview of the Irtysh River basin

Overview of the Irtysh River basin

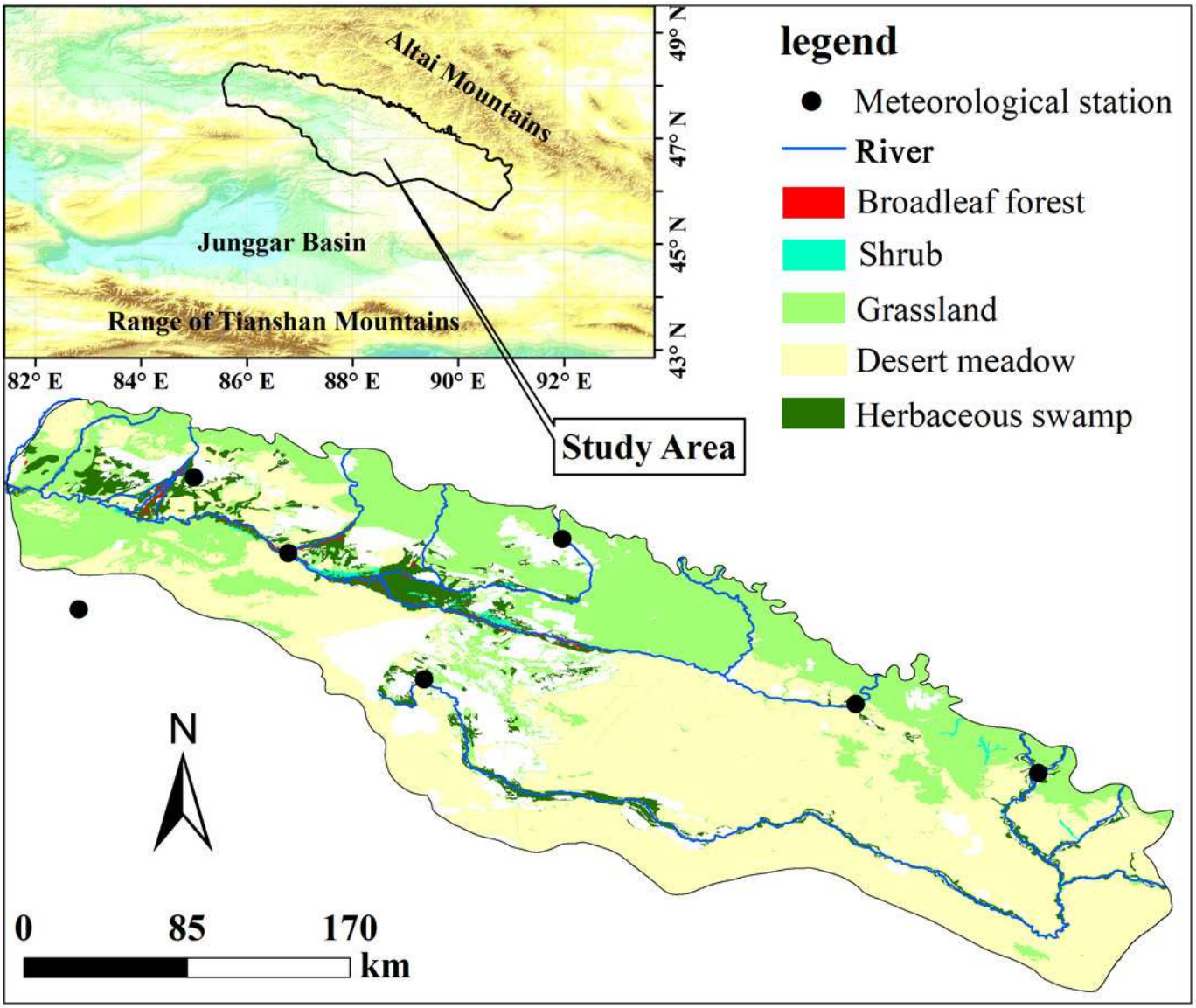


Figure 2

Distribution map of annual average NDVI levels, NDVI change trend Zc value and change rate β value

(A) Distribution map of annual average NDVI levels in the study area from 2000 to 2018 and Spatial distribution of variance in vegetation cover; (B) NDVI change trend Zc value and (C) change rate β value spatial distribution map. Characterizing change trend of each vegetated pixel in the study area.

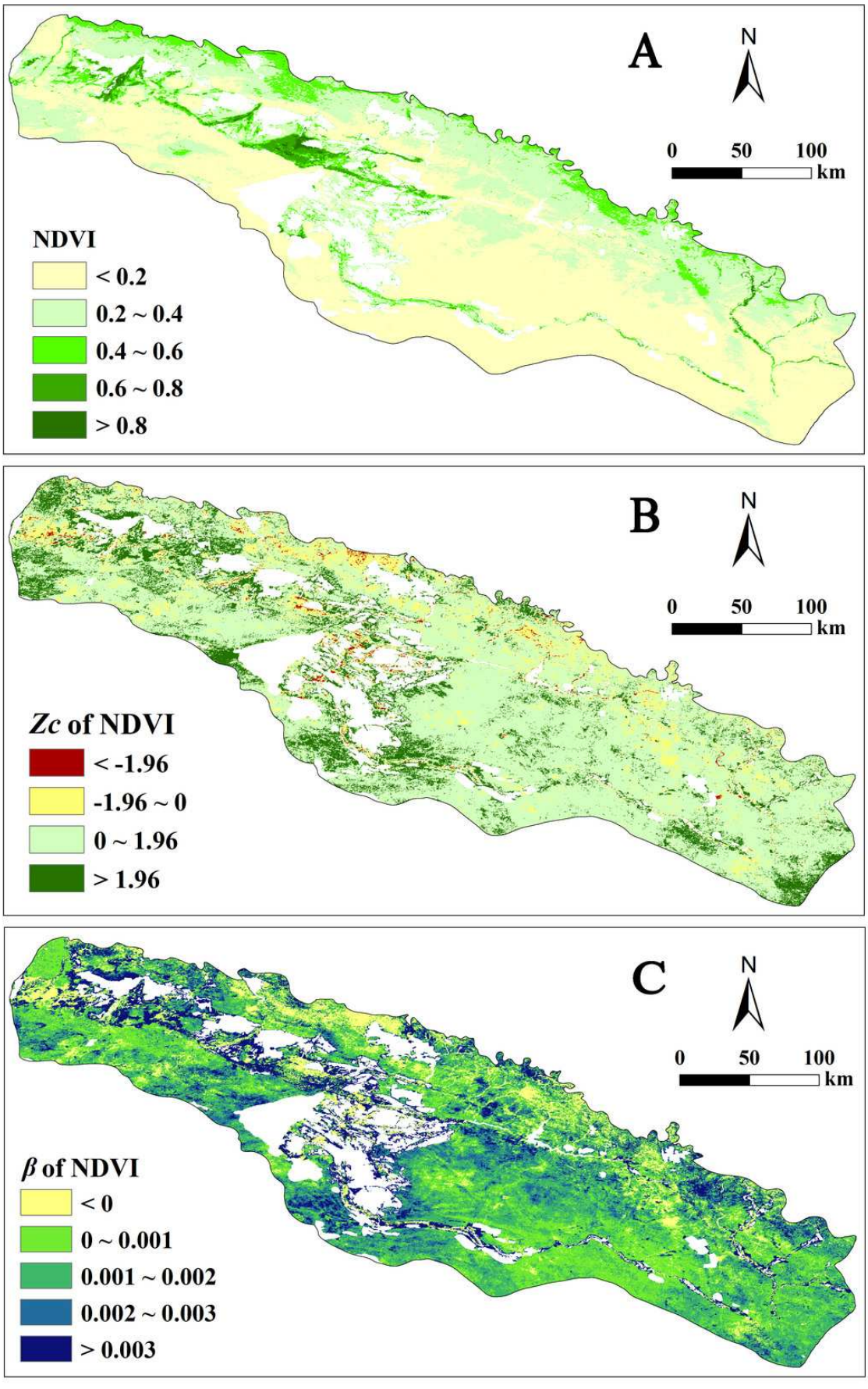

A
N
0 50 100
km
NDVI
< 0.2
0.2 ~ 0.4
0.4 ~ 0.6
0.6 ~ 0.8
> 0.8
B
N
0 50 100
km
Zc of NDVI
< -1.96
-1.96 ~ 0
0 ~ 1.96
> 1.96
C
N
0 50 100
km
β of NDVI
< 0
0 ~ 0.001
0.001 ~ 0.002
0.002 ~ 0.003
> 0.003

Figure 3

Interannual variation curve of overall NDVI in the study area from 2000 to 2018.

Interannual variation curve of overall NDVI in the study area from 2000 to 2018.

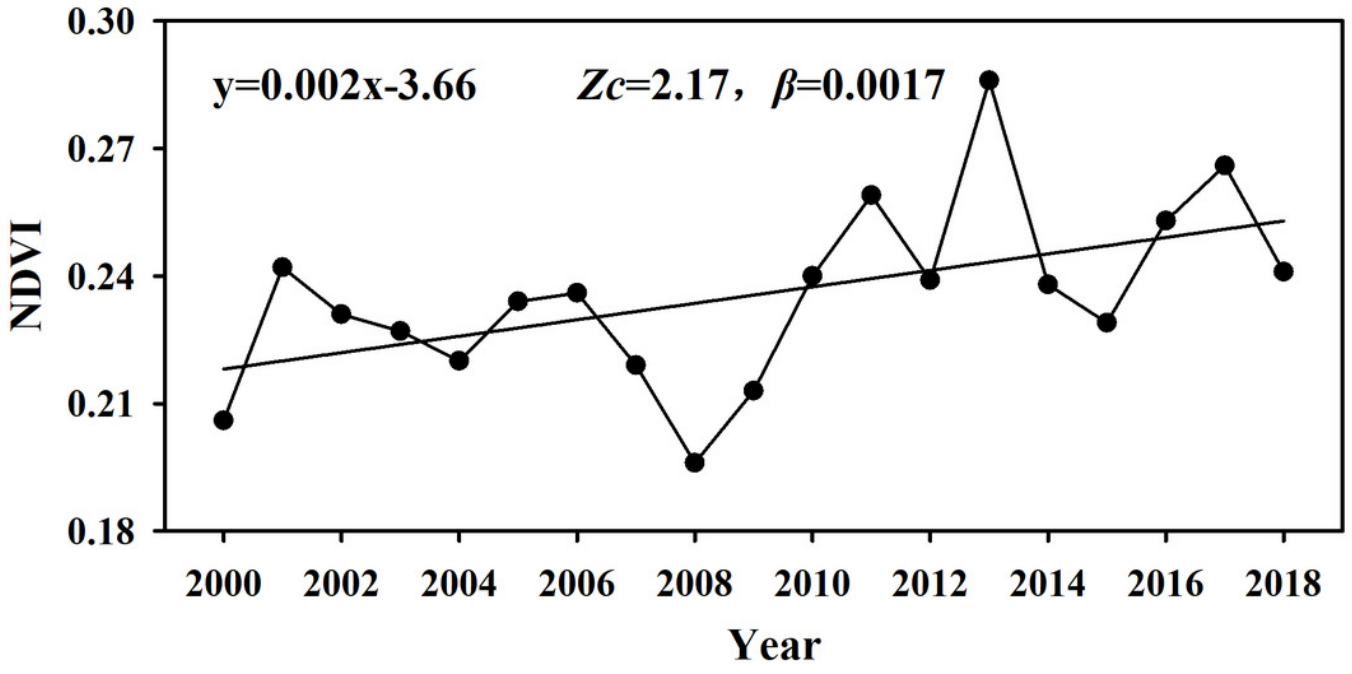


Figure 4

Interannual variation curves of overall precipitation, temperature, and TVDI in the study area from the period 2000-2018.

Interannual variation curves of overall precipitation (A), temperature (B), and TVDI (C) in the study area from the period 2000-2018.

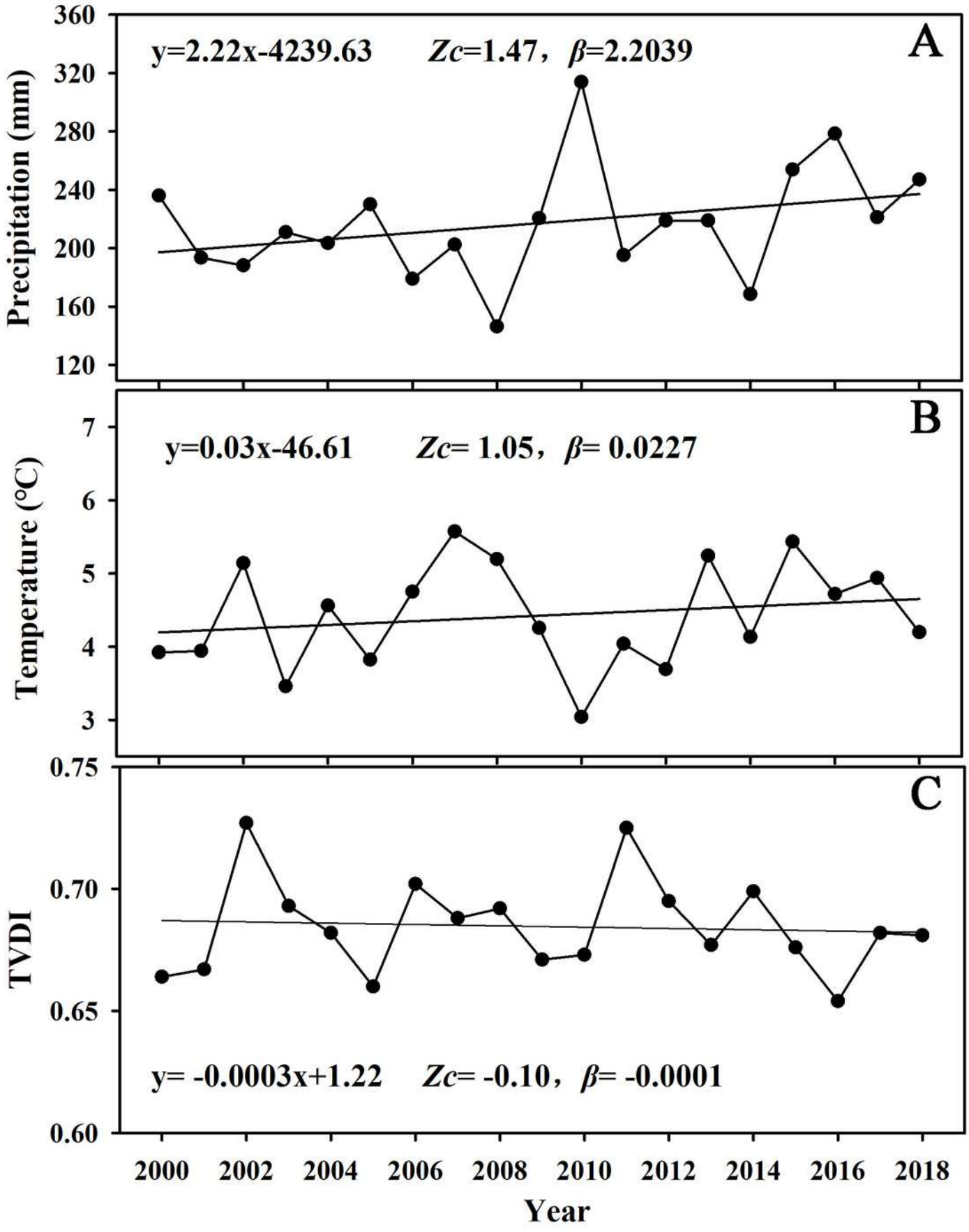

A
y=2.22x-4239.63
Zc=1.47, β=2.2039
Precipitation (mm)
360
320
280
240
200
160
120
B
y=0.03x-46.61
Zc= 1.05, β= 0.0227
Temperature (°C)
7
6
5
4
3
C
y= -0.0003x+1.22
Zc= -0.10, β= -0.0001
TVDI
0.75
0.70
0.65
0.60
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018
Year

Figure 5

Spatial distribution of t-1 (AR1) coefficient weight

Spatial distribution of t-1 (AR1) coefficient weight (that is, coefficient α) from monthly multiple regression between vegetation cover (defined as NDVI), vegetation cover at t-1, and three climatic variables. Characterizing the memory effects of vegetation cover in the Irtysh River basin during 2000-2018.

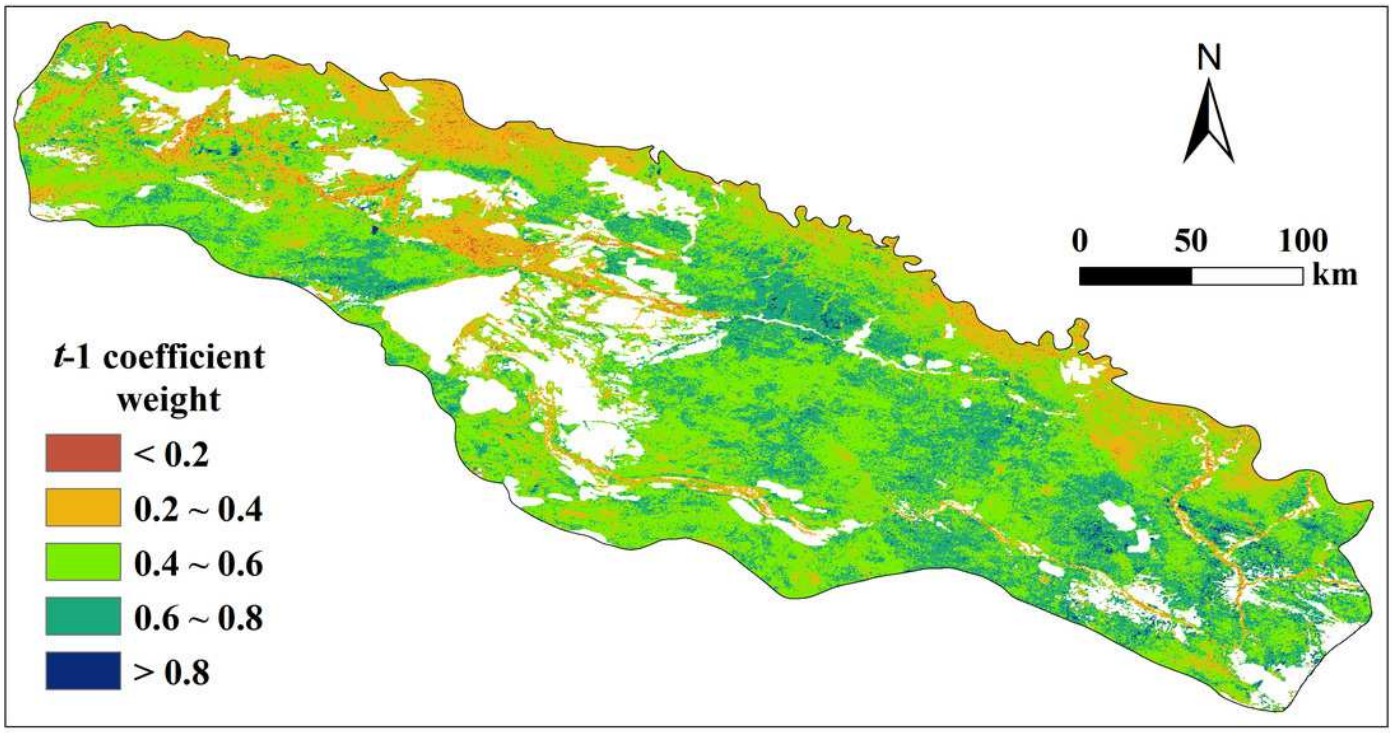


Figure 6

Correlations between α (t-1 coefficient weight) and mean growing season climatic factors

Correlations between α (t-1 coefficient weight) and mean growing season (A)NDVI, (B)precipitation, (C)temperature, (D)TVDI in the Irtysh River basin during 2000-2018. The green curves indicate the fitted regression lines.

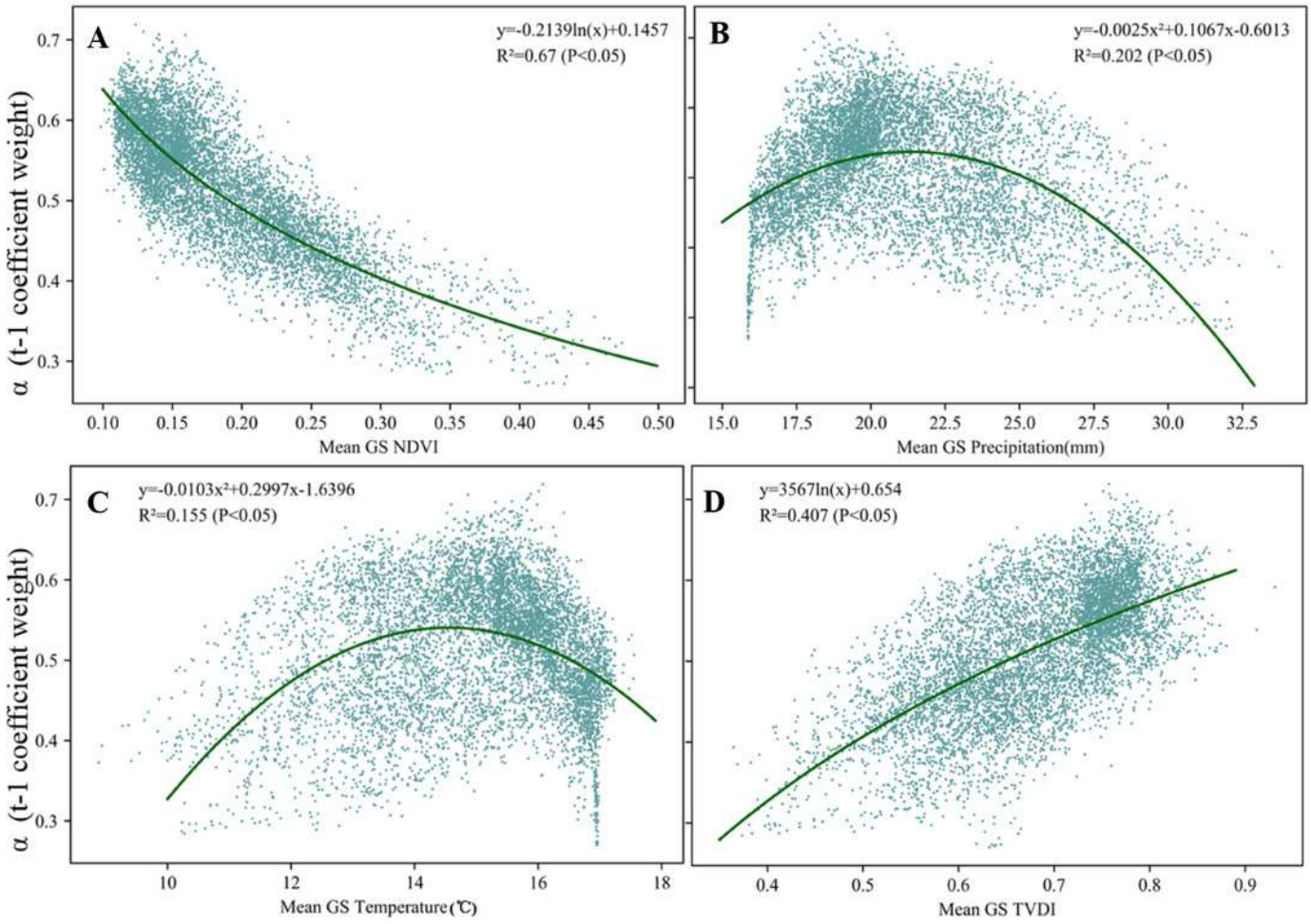
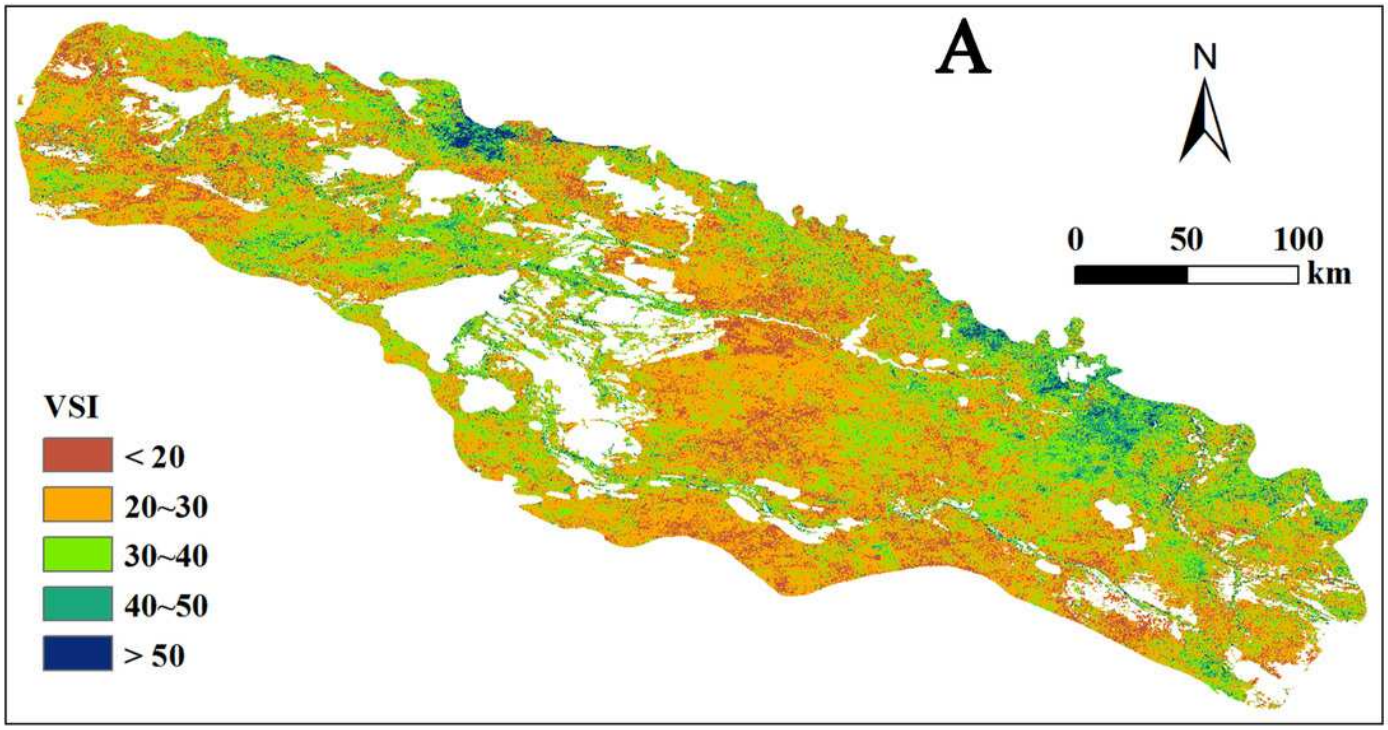


Figure 7

Distribution of Vegetation sensitivity index (VSI) in Irtysh River basin during 2000-2018

(A) Spatial distribution of Vegetation sensitivity index (VSI) in Irtysh River basin during 2000-2018. The index ranges from 0(low sensitivity) to 100(high sensitivity). (B) VSI distribution histogram, insert panel of violin plot shows the frequency distribution of pixel VSI values.


A
N
0 50 100
km
VSI
< 20
20~30
30~40
40~50
> 50

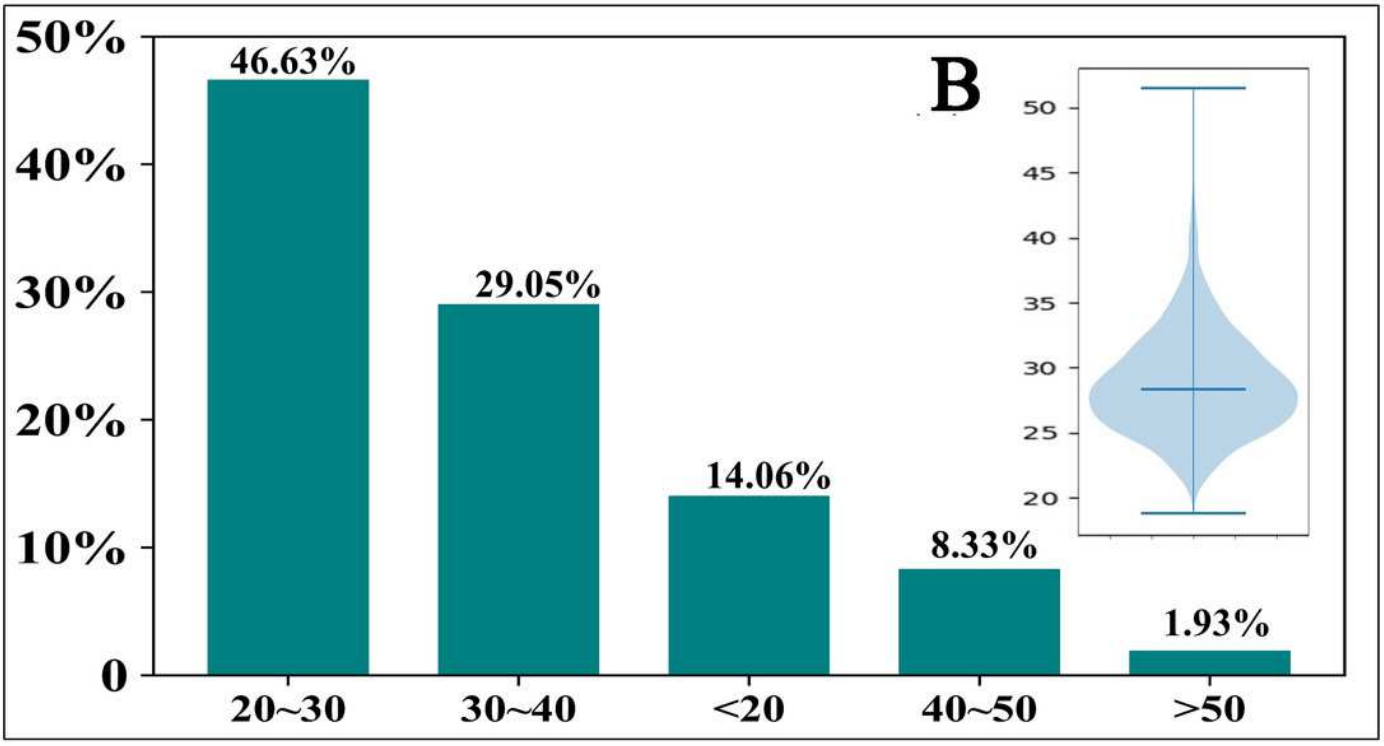

B
50%
40%
30%
20%
10%
0
46.63%
29.05%
14.06%
8.33%
1.93%
20~30
30~40
<20
40~50
>50
50
45
40
35
30
25
20

Figure 8

RGB composite of climate weights

RGB composite of climate weights from monthly multiple regression between vegetation cover (defined as NDVI), vegetation cover at t-1, and three climatic variables. Notably, temperature, red; TVDI, green; and precipitation, blue.