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Effects of Precipitation Intensity and Temperature on NDVI-Based Grass Change over Northern China during the Period from 1982 to 2011

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Abstract: The knowledge about impacts of changes in precipitation regimes on terrestrial ecosystems is fundamental to improve our understanding of global environment change, particularly in the context that heavy precipitation is expected to increase according to the 5th Intergovernmental Panel on Climate Change (IPCC) assessment. Based on observed climate data and the Advanced Very High Resolution Radiometer (AVHRR) Global Inventory Modeling and Mapping Studies (GIMMS) satellite-derived normalized difference vegetation index (NDVI), here we analyzed the spatio-temporal changes in grassland NDVI, covering $1.64 \times 10^6 \, \mathrm{km^2}$, in northern China and their linkages to changes in precipitation and temperature during the period 1982–2011. We found that mean growing season (April–October) grass NDVI is more sensitive to heavy precipitation than to moderate or light precipitation in both relatively arid areas (RAA) and relatively humid areas (RHA), whereas the sensitivities of grass NDVI to temperature are comparable to total precipitation in RHA. Heavy precipitation showed the strongest impacts in more than half of northern China (56%), whereas impacts of light precipitation on grass NDVI were stronger in some areas (21%), mainly distributed in northwestern China, a typical arid and

semi-arid area. Our findings suggest that responses of grasslands are divergent with respect to changes in precipitation intensities.

Keywords: climate change; GIMMS; NDVI; precipitation intensity

1. Introduction

The response of terrestrial ecosystems to climate change is one of the important themes in current global environmental change research [1–3]. Vegetation, as an active component of ecosystems, which links soil and atmosphere through energy and mass transports [4,5], is taken as a comprehensive indicator of global change. Grassland in northern China is one of the world's three largest prairies and is regarded as typical vegetation in responding to climate changes [6]. Previous studies showed that the climate in this region has experienced dramatic change in the past several decades, leading to significant vegetation changes [7,8]. The amount of annual precipitation is identified as the most important factor for annual variations in normalized difference vegetation indices (NDVI) [9,10].

NDVI can sensitively reflect the growth conditions of vegetation and the biophysical or biochemical characteristics of ecosystems [11]. Thus, NDVI has been widely used to investigate the impacts of climate variables on ecosystem functioning and dynamics. Previous studies indicated that responses of grassland NDVI to precipitation in China differed across biome types and the amount of precipitation [12] and also differed at different time-scales [13,14]. Grasslands in arid regions may be more sensitive to precipitation fluctuations than those grasslands in humid regions [15], and this sensitivity becomes weak as the altitude increases [16]. At an annual time-scale, precipitation is the main factor of driving grass NDVI changes [14,17]. At seasonal time-scale, the sensitivity of grass NDVI to precipitation is higher in summer than in other seasons [10,18]. Effects of precipitation on vegetation show obvious time lag as well, which can last several days to several months [17,19–21]. The preceding winter precipitation also influences the following growing season NDVI in northwestern China [22]. Besides precipitation, temperature is another important factor influencing vegetation activity [1,17]. Over northern China, the positive effects of temperature on the growth of grasslands decrease as temperature rises, implying that the sensitivity of vegetation growth to temperature in high-cold regions may decline under global warming [23]. In high altitude regions, temperature rather than precipitation controls vegetation growth [16]. In North America, the increasing trend of spring vegetation greening stalled or reversed maybe due to the corresponding reverse trend of spring temperature [24]. The response of grass NDVI to temperature shows high latitudinal dependence, and the importance of temperature increases with the increase in latitude [25]. Additionally, grass NDVI could show significant correlation with other factors, such as winter snow depth [26], potential evapotranspiration [10], and nutrient availability [27].

An increasing trend of grass NDVI is observed in northern China [8,18,28], characterized as the advancement of greening or extension in growing season period [8]. To reveal the responses of vegetation to climate change in northern China, many studies have investigated the relationships between grass NDVI and climate factors, particularly precipitation [14,23,29]. However, most of these studies focused mainly on how grass NDVI varies with the total growing-season or annual precipitation.

Precipitation is characterized not only by the total amount of precipitation but also by the frequency (number of precipitation events in a year) and the intensity (amount in each precipitation event) [30]. Joint effects of frequency and intensity cause variations of precipitation in a given time period. In northern China, changes in annual precipitation are mainly caused by heavy precipitation, particularly in northwestern China [30–33]. Therefore, significant changes in precipitation intensity are expected to have important effects on terrestrial ecosystems. In this paper, we used observed climate data and satellite derived NDVI to investigate the sensitivities of grass NDVI changes to growing season temperature (GST) and precipitation intensity in northern China during the period 1982–2011. The specific goal is to reveal the divergent effects of precipitation of different intensities, in conjunction with temperature, on grassland vegetation activities, which will improve our understanding in interactions between terrestrial ecosystem and climate.

2. Data and Methods

2.1. Study Area

The study area encompasses 13 provinces in northern China (31 N-54 N, 73 \mathbb{E}-136 \mathbb{E}; Figure 1), and the grassland area of these regions is 1.64×10^6 km², comprising nearly 17% of China's territory [23]. The grassland area was extracted by using the MODIS (Moderate Resolution Imaging Spectroradiometer) land cover type product (MCD12C1.005) in 2005 at a spatial resolution of 0.05 ° and the classification method was according to the International Geosphere—Biosphere Program (IGBP) (Figure 1A), and the agriculture and other land cover types were removed. The area covers three types of climate, i.e., temperate monsoon climate, temperate continental climate and alpine climate. The northeast of the study region (NE) is strongly influenced by temperate monsoon climate, where the rain season occurs in summer (June-August). The annual precipitation is about above 450 mm and the annual mean temperature varies from −3 °C to 9 °C in NE [34]. The altitude was lower than 1000 m and grassland is dominated by meadow steppes. The northwest of this study region (NW) is characterized by temperate continental climate. The annual precipitation decreases from east to west precipitation, ranging from more than 400 mm in the east to less than 100 mm in the west and the annual mean temperature ranges from -5 to 15 °C. Following this east-to-west precipitation gradient, the grass types change from typical steppes to desert steppes. Altitude ranges from -150 m in Qaidam basin to more than 2000 m in mount Tianshan. The southwest of the study region (SW) is located in Qinghai Plateau, strongly influenced by alpine climate. The mean altitude was 4054.3 m, which leads to annual mean temperature lower than 0 °C, and the annual mean precipitation ranges from 100 to 700 mm from southeast to northwest and grass type is characterized by alpine steppes and alpine meadow [35].

2.2. GIMMS Data and Processing

The latest version of GIMMS (Global Inventory Modeling and Mapping Studies) NDVI3g dataset at a spatial resolution of 1/12 degree and a 15-day time-step was downloaded from the Ecological Forecasting Lab at NASA Ames Research Center [36]. The NDVI dataset covered from January 1982 to December 2011, and 720 images were used in this study. The dataset is well known for its long time

series and high quality, which has been processed by radiometric and geometric crude correction, geometric refined correction and bad lines removing. Therefore, the data have been widely used in studies on global and regional vegetation dynamics [37,38]. To further reduce the contamination of clouds, atmosphere, and non-grassland vegetation, the method of maximum value composite [39] was used to extract monthly NDVI and the cells with mean annual NDVI values of less than 0.1 were ignored.

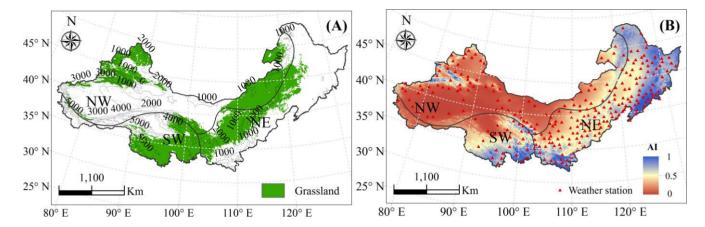


Figure 1. Distribution of grasslands (**A**) and aridity index (AI) (**B**) in northern China. The green color area represents grasslands extracted from the MODIS global land cover dataset in 2005 and the gray lines represent elevation contour. The red color triangles indicate weather stations. The study area was divided into three climate zones, the northeastern part (NE), influenced by temperate monsoon climate, the northwest part (NW), influenced by temperate continental climate and the southwest part (SW), influenced by alpine climate.

2.3. Meteorological Data and Processing

The station observed daily precipitation and temperature data from 1982 to 2011 were obtained from China Meteorological Data Sharing Service System [40]. Meteorological stations established after 1982 were discarded and finally 629 well spatially distributed stations in China were used. In addition, 271 stations are located within our study area (Figure 1B). The dataset consists of daily measurements of precipitation and temperature, so precipitation intensities and frequencies can be easily calculated. In order to explore the spatio-temporal variations of precipitation and temperature and the relationships between grass NDVI and precipitation and temperature, the inverse distance and elevation weighting (IDEW) method was used to interpolate site-measured climate data to a spatial domain at a 1/12 degree resolution, for consistency with NDVI dataset. Further information on the spatial interpolation method can be found in Liston *et al.* [41]. For daily interpolation, the IDEW method has been proved to be satisfactory in northern China, where the elevation has wide ranges from -150 to 8000 m [42,43].

2.4. Definition of Precipitation Intensity

Precipitation intensity was defined as the amount of precipitation in one day. According to the value of daily precipitation, it was grouped into three levels: light, moderate and heavy precipitation. There are many different approaches for defining precipitation intensity levels. The first approach is to use

"ad hoc" threshold values to identify precipitation intensity levels [44,45]. For example, one can define precipitation intensity less than 5 mm day⁻¹ as light, 5~10 mm day⁻¹ as moderate and larger than 10 mm day⁻¹ as heavy precipitation [46]. The disadvantage of this method is the randomness of the choice of the "ad hoc" threshold values. The second approach is based on percentiles of precipitation distribution. Low percentiles of precipitation are identified as light precipitation and high percentiles of precipitation as heavy precipitation [47]. This approach is particularly useful for investigating the extremes of precipitation but suffers similar problems in quantifying the level thresholds of precipitation intensity. The third approach is to categorize the precipitation intensity into several bins for categorizing precipitation intensity levels [48]. For example, Alpert et al. [49] divided daily precipitation into six bins by values in powers of 2 to define different precipitation intensity levels from light to torrential. Osborn et al. [50] divided precipitation intensities into 10 levels and each level contributed 10% to the total precipitation. In this study, the maximum boundary of precipitation intensity was firstly determined as the minimum value of largest precipitation intensity in each year during the period 1982–2011. The value of the maximum boundary of precipitation intensity was divided into three equal sections and two threshold values could be determined. The two threshold values corresponding to the precipitation intensity were used to define light, moderate and heavy precipitation, respectively.

Given large spatial variations of precipitation over northern China, the aridity index was used to divide the study area into relatively arid areas (RAA) and relatively humid areas (RHA) to distinguish different precipitation regimes. The aridity index was downloaded from the global aridity and potential evapotranspiration database [51] (Figure 1B). Relatively arid areas were identified as the regions with aridity index less than 0.5 and relatively humid areas as the regions with aridity index larger than 0.5 [52]. The mean annual precipitation is about 80–300 mm in RAA and about 300–450 mm in RHA. Either RHA or RAA accounts for about half the area of northern China, according to our classification method (0.8 million km² in RHA, and 0.9 million km² in RHA, respectively). The analysis showed that the values of maximum boundary of precipitation intensity are 17 mm day⁻¹ and 14 mm day⁻¹ in RHA and RAA, respectively. Therefore, light, moderate and heavy precipitation were defined as three intervals of daily precipitation <5.67, 5.67–11.33 and >11.33 mm day⁻¹ in RHA and <4.67, 4.67–9.33 and >9.33 mm day⁻¹ in RAA, respectively.

2.5. Statistical Indicators

A linear fitting method was used to compute the trend of time series of grassland NDVI, precipitation and temperature. The Pearson's correlation (r) was used to analyze the correlation between NDVI and climate variables at a 0.05 significance (p) level. The standardized form of quasi-Gaussian probability distribution was used to describe the effects of different precipitation intensities on NDVI changes.

To make environment drivers of different dimensions comparable, all variables were normalized using the following formula:

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where X is a variable (NDVI, GST, annual precipitation and different precipitation intensities), X_n is the normalized value, and X_{max} and X_{min} are the maximum and minimum values of variables, respectively, during the period 1982–2011. The temporal interval accounting for NDVI and temperature is the growing season (April–October), whereas the temporal interval for precipitation counted from last November to this October in a specific year. This was to take into account the lagging effect of precipitation on vegetation [12].

To assess the sensitivity of grass NDVI to GST and precipitation intensity, we regressed the normalized NDVI with normalized GST and precipitation intensities (H, M, and L are normalized heavy, moderate and light precipitation, respectively):

$$NDVI = a_1H + a_2M + a_3L + a_4GST + \varepsilon_1$$
 (2)

where a_1 , a_2 , a_3 and a_4 are regression coefficients, and ε_1 is the residual error.

In order to examine the effects of total precipitation and GST on NDVI, a multiple linear regression was also performed using normalized NDVI and total precipitation (P) and GST:

$$NDVI = b_1P + b_2GST + \varepsilon_2 \tag{3}$$

where b_1 and b_2 are regression coefficients, and ε_2 is the residual error. We defined the regression coefficients as the sensitivities of grass NDVI to different climate variables, respectively.

3. Results

3.1. Temporal and Spatial Trends of NDVI, Precipitation and GST

Figure 2 shows the temporal trend of mean growing season NDVI, annual precipitation, GST, and heavy precipitation during the period from 1982 to 2011. NDVI increased significantly ($r^2 = 0.22$, p < 0.01, Figure 2A) from 0.32 in 1982 to 0.35 in 2011 with an increasing rate of 0.0005 year⁻¹. Total precipitation showed a slight but not significant decrease $r^2 = 0.19$, p = 0.43, Figure 2B), whereas heavy precipitation showed a slight increase ($r^2 = 0.02$, p = 0.46, Figure 2C) though not significant. Mean growing season temperature increased significantly over the past three decades, with an average increase of 0.05 °C year⁻¹ ($r^2 = 0.68$, p < 0.01, Figure 2D).

Figure 3 illustrates the spatial change rates of grassland NDVI, precipitation and GST during the period 1982–2011. The majority of grassland in northern China (69% pixels) experienced an increase in NDVI, and 31.2% pixels were significantly mostly in southwest NE and northwest NW. The rate of increase in NDVI could exceed 0.004 year⁻¹ in some pixels. About one third of grasslands underwent a decrease in NDVI, but only 5% pixels were significant, such as in a small regions of northeast of NE. The rate of decrease in NDVI was relatively low at a value of -0.002 year⁻¹ (Figure 3A). For precipitation, there were two contrasting trends between the east and the west of northern China. In the east, precipitation was dominated by a decreasing trend (13% pixels), with an average rate of -1.9 mm·year⁻¹, such as the entire NE and the east of NW, while in the west, precipitation showed an increasing trend (12% pixels), with an average rate of 1 mm year⁻¹ such as the entire SW and the west of NW. GST increased over the study area (99% pixels) at the average rate 0.05 °C year⁻¹.

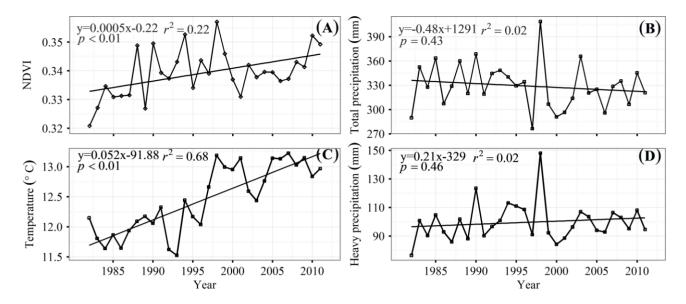


Figure 2. Dynamics of mean growing season (April–October) NDVI (**A**); annual precipitation (**B**); mean growing season temperature (**C**); and heavy precipitation (**D**) over northern China during the period 1982–2011. Straight lines indicate linear regressions of NDVI, precipitation, temperature and heavy precipitation against the time period, respectively.

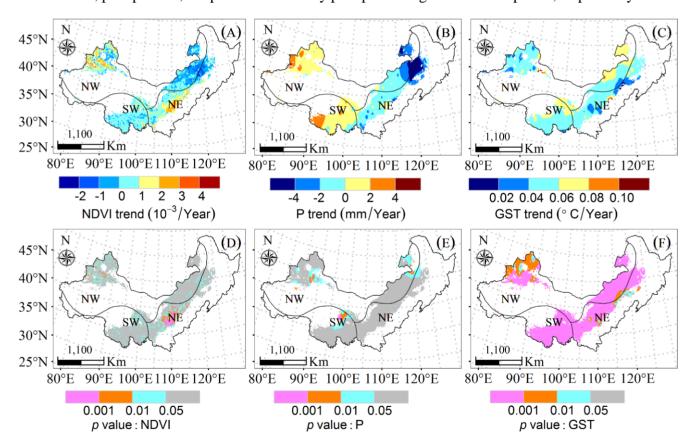


Figure 3. Changes in mean growing season NDVI (**A**); annual precipitation (P) (**B**); growing season temperature (GST) (**C**); and the corresponding statistical p values for NDVI change (**D**); precipitation change (**E**); and GST change (**F**), respectively, in northern China during the period 1982–2011.

3.2. Response of NDVI to Precipitation and GST

Figure 4 shows the spatial r values and corresponding p values between the change in mean growing season NDVI and the change in precipitation and temperature during the period from 1982 to 2011. It was found that 82.6% of grass NDVI showed positive response to precipitation and 30.2% pixels were significant (p < 0.05 pink, red and light blue in Figure 4B). In addition, 17.4% of grass NDVI showed negative correlation with precipitation but only 0.8% pixels were significant (p < 0.05). The positive r values were mainly distributed in NE, NW and northeast of SW. The negative r values were mainly located in the southwest of SW, where the average altitude is higher than 4000 m where positive correlation between NDVI and GST was located. Furthermore, 66% of grass NDVI showed negative correlation with GST, but only 2% of pixels were significant (p < 0.05, light blue in Figure 4D), mainly distributed in the northeast of NE and northwest of NW.

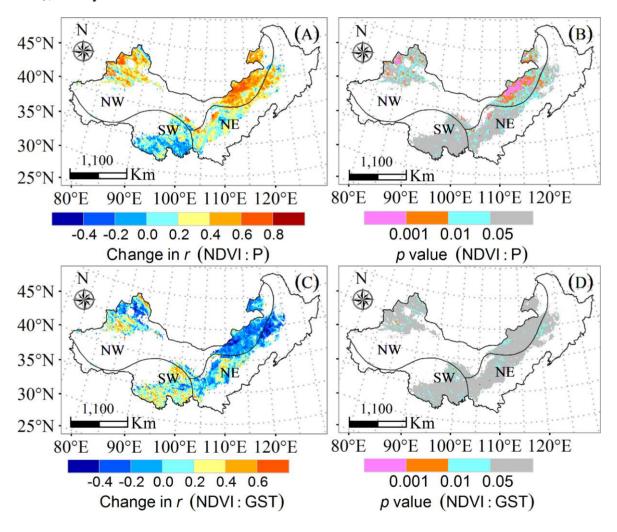


Figure 4. The distribution of spatial correlation coefficients (r) (**A**) and the corresponding p values (**B**) between mean growing season grass NDVI and annual precipitation (P), and the distribution of spatial r (**C**) and corresponding statistical p values (**D**) between mean growing season grass NDVI and mean growing season temperature (GST).

3.3. Sensitivities of NDVI to GST and Precipitation Intensity

Table 1 shows the sensitivities of NDVI to different precipitation intensities and GST. The sensitivity of NDVI to heavy precipitation was larger than to moderate or light precipitation. The sensitivities of NDVI to light and moderate precipitation were almost equivalent in both RAA and RHA. In RAA, the sensitivity of NDVI to temperature (0.13) was less than that to any of precipitation intensities (0.23, 0.2 and 0.37 for light, moderate and heavy precipitation, respectively) and also less than that to total precipitation (0.39). In contrast, in RHA, the sensitivity of NDVI to temperature (0.21) was larger than that to any of precipitation intensities (0.06, 0.11 and 0.19 for light, moderate and heavy precipitation, respectively), but it (0.21) was comparable to that of total precipitation (0.24). As shown in Figure 4A, grassland NDVI could be either positively or negatively correlated with precipitation in different regions. The r between NDVI and precipitation ranged from -0.68 to 0.83 for all pixels, and showed a quasi-Gaussian probability distribution with a mean r value of 0.16 (± 0.23) and 0.37 (\pm 0.21), respectively, in RHA and RAA (Figure 5Bottom). The majority of r values (92.7% in RAA and 70.2% in RHA) were positive (p < 0.01), indicating that NDVI was positively correlated with precipitation. The mean r values between NDVI and heavy precipitation was 0.17 ± 0.20 and $0.3~(\pm 0.20)$ in RHA and RAA, respectively, comparable with mean r values between NDVI and total precipitation (Figure 5Top). This indicated that heavy precipitation played an almost equivalent role as the total precipitation in explaining NDVI variations. In contrast, moderate and light precipitation produced quasi-Gaussian probability distribution with a mean r of 0.04 and 0.09 in RHA (Figure 5Left) and 0.16 and 0.17 in RAA (Figure 5Right). As shown in Figure 5, both moderate and light precipitation fitted Gaussian curves were visibly shifted to the left (p < 0.05), indicating that the correlation between grassland NDVI and precipitation became weak. The two fitted curves from moderate and light precipitation were obviously different from the curves from heavy precipitation or total annual precipitation. It suggested that heavy precipitation had stronger impacts than moderate or light precipitation on NDVI in some areas.

Table 1. Sensitivities (mean \pm standard deviation) of normalized difference vegetation index (NDVI) to different intensity precipitation (heavy precipitation, a_1 ; moderate precipitation, a_2 ; light precipitation, a_3) and growing season temperature (GST) (a_4), acquired by equation (2), and sensitivities of NDVI to total precipitation (b_1) and GST (b_2) acquired by equation (3) in relative humid areas (RHA) and relative arid areas (RAA), respectively. The p values were calculated pixel-by-pixel for each equation, and the percentage (Perc) of pixels of significance at p < 0.05 was listed.

Region		Precipitation	Total Precipitation and GST					
	a_1	a_2	a_3	a_4	Perc	b_1	b_2	Perc
RAA	0.37 ± 0.23	0.2 ± 0.21	0.23 ± 0.25	0.13 ± 0.26	57%	0.39 ± 0.22	0.13 ± 0.25	64%
RHA	0.19 ± 0.23	0.11 ± 0.24	0.06 ± 0.29	0.21 ± 0.3	47%	0.24 ± 0.29	0.21 ± 0.3	56%

There are also a large number of pixels showing higher r values between NDVI and light or moderate precipitation than that between NDVI and heavy precipitation (Figure 6). Those pixels with higher r (21%) between NDVI and light precipitation were mainly distributed in northwestern NW,

and the pixels with higher r (23%) between NDVI and moderate precipitation were distributed irregularly compared with r values between NDVI and heavy precipitation (Figure 6A–C). Over northern China, more pixels (56%) showed higher r between NDVI and heavy precipitation than that between NDVI and light or moderate precipitation, which were mainly distributed in the east of NW and NE. Spatial patterns of r between NDVI and heavy precipitation (Figure 6C) were very similar to those of r between NDVI and total precipitation (Figure 4A), and the positive r accounted for 82.5% of pixels, very close to total precipitation (82.6%). In contrast, light and moderate precipitations contributed 67% and 70% of pixels with positive r. Those pixels with negative r between NDVI and precipitation were mainly distributed in SW, where the mean altitude is higher than 4000 m. However, pixels in these high altitude regions, showed positive r values between NDVI and temperature, accounting for 34% of northern China (Figure 4C), indicating that the temperature was the main factor of driving grass NDVI changes in high altitude areas.

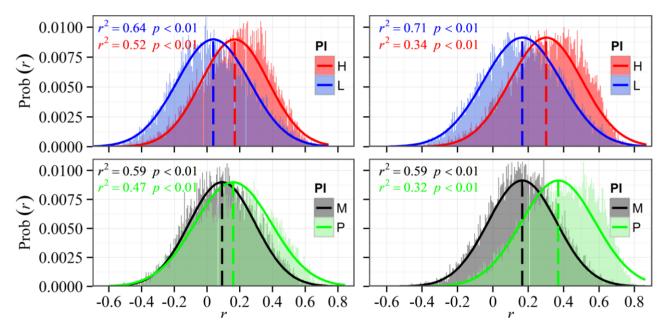


Figure 5. Gaussian probability distributions (Prob(*r*)) of Pearson correlation coefficient (*r*) between the mean growing season NDVI and different intensities of precipitation (PI) (heavy precipitation, H; light precipitation, L; top panel. Total precipitation, P; moderate precipitation, M; bottom panel). Light, moderate and heavy precipitations were defined as the amount of received precipitation of less than 5.67 mm per day, between 5.67 and 11.33 mm per day, and larger than 11.33 mm per day, respectively, in relatively humid areas (RHA) (**Left**). Light, moderate and heavy precipitations were defined as the amount of received precipitation of less than 4.67 mm per day, between 4.67 and 9.33 mm per day, and larger than 9.33 mm per day, respectively, in relative arid areas (RAA) (**Right**). The red, and blue lines at top panel indicate fitted Gaussian probability distributions curve lines for *r* between grass NDVI and heavy and light precipitation, respectively; the green and black lines at bottom panel indicate fitted Gaussian probability distributions curve lines for *b* between grass NDVI and total and moderate precipitation, respectively.

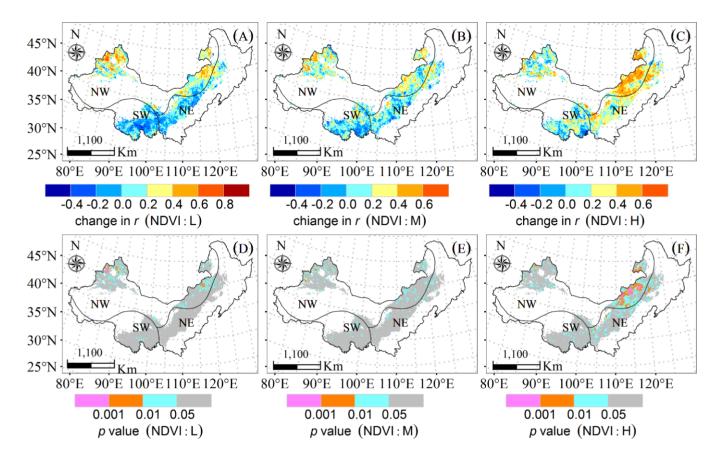


Figure 6. Distributions of correlation coefficients (r) between NDVI and light (L, A), moderate (M, B), and heavy (H, C) precipitation, and the corresponding statistical p values between NDVI and light (D), moderate (E), and heavy precipitation (F), respectively, in northern China during 1982–2011.

4. Discussion

4.1. Response of Grass NDVI to Precipitation and GST

Our results show that grass NDVI tended to increase mainly due to the increases in precipitation, while temperature showed limited effects on the change in grassland NDVI in the western part of NW and southwestern part of NE. Peng *et al.* [53] suggested that the amount of precipitation could explain 70% of variations of NDVI in grasslands in arid and semi-arid environments and the increase in precipitation would promote the growth of grasslands. This is true in the western part of NW. However, in the southwestern part of NE, grass NDVI increased under the condition precipitation decreased (Figure 3A,B). The possible reason may be linked to temperature influencing changes in grass NDVI over northeastern China. The correlation between grass NDVI and precipitation typically varied with precipitation in nonlinear, mostly a downward parabola curve, which means that a most sensitive value of precipitation is existed, and the most sensitive value is about 250 mm [23,54]. The dependence of grass vegetation on precipitation becomes weak when precipitation exceeds 250 mm, but the annual mean precipitation in the southwestern part of NE is larger than 300 mm, indicating that rainfall was not the main limiting factor for grass NDVI, and the increase in grass is more related to temperature. Although precipitation decreased, the amount of precipitation was still larger than the

most sensitive value of precipitation (250 mm), and increased temperature also advances the beginning of the vegetation growing season and accelerates vegetation growth [8]. Consequently, the mean grassland NDVI still showed an increasing trend. In those areas where precipitation increased, the increase in grassland NDVI was deemed as a result of the increase in precipitation in the western part of northern China, typically arid and semi-arid regions.

4.2. Response of Grass NDVI to Precipitation Intensity

Several model-based and experimental studies have shown that the growth of grassland responds strongly to extreme or heavy precipitation [15,46,55], which are consistent with our results but not true in areas at high altitudes, especially in Tianshan mountains, Altai mountains and Qinghai Plateau. The effects of temperature and precipitation on vegetation growth are different in different geographic regions or different grasslands [18,56]. In high altitude regions, the growing season NDVI was significantly and more strongly correlated with the GST rather than annual precipitation (Figure 5), implying that temperature is the dominant climate factor regulating vegetation growth in these areas. This result is consistent with previous findings by Mohammat *et al.* [16]. The reason may be that lower temperatures lead to less evaporation and weakened photosynthesis. Therefore, the dependence of growth of vegetation on precipitation decreased, especially for Qinghai Plateau, where the mean elevation is 4054.3 m.

Furthermore, it is generally believed that if heavy precipitation contributes the majority of total precipitation, it is easy to deduce a higher r between heavy precipitation and NDVI compared with r between NDVI and moderate or light precipitation. So we calculated the proportions of different intensity precipitation in the total precipitation (Table 2). The heavy precipitation accounted for only 25.9% and 37% in RHA and RAA respectively, while the light precipitation accounted for most, 46.3% and 39.9% in RHA and RAA, respectively. The mean values of r between grass NDVI and total precipitation, 0.37 (\pm 0.21) in RAA, 0.16 (\pm 0.23) in RHA, are comparable with r values between grass NDVI and heavy precipitation, 0.3 (± 0.20) in RAA, 0.17 (± 0.20) in RHA. In addition, the sensitivities of grass NDVI to total precipitation are 0.37 (±0.23) in RAA and 0.19 (±0.23) in RHA, which are comparable to sensitivities of grass NDVI to heavy precipitation with 0.39 (±0.22) in RAA and 0.24 (±0.29) in RHA. Both correlation values and sensitivities between grass NDVI and total or heavy precipitation are larger than those between grass NDVI and light or moderate precipitation. Our analysis shows that different intensity of precipitation (light, moderate, and heavy precipitation) exerts divergent impacts on grass NDVI, and heavy precipitation had stronger effect on grass NDVI than light or moderate precipitation. The results indicated that heavy precipitation played an almost equivalent role as total precipitation in explaining grass NDVI variation in our study.

Our studies indicated that light precipitation (4.67 mm and 5.67 mm in RAA and RHA, respectively) had limited effects on NDVI, consistent with previous report that lower than 5 mm of precipitation had no significant influence on grass NDVI [57]. In most parts of northern China, vegetation growth is limited by water availability [58,59]. Associated high temperature and solar radiation led to high atmospheric evaporation demand, and evaporated that water of light precipitation events directly from land surface, so light precipitation was essentially ineffective for grass growth [57,60]. Previous studies have reported that soil moisture below 20 cm of the soil surface did

not significantly change when precipitation was less than 15 mm [60], which is in support of the results derived in this study. In addition, the annual precipitation frequencies for light and moderate precipitation account for 87% and 9% in RHA, and 86.2% and 8.4% in RAA respectively, which are much larger than heavy precipitation frequencies with 3.7% in RHA and 5.4% in RAA (Table 2). In contrast, heavy precipitation has a much larger cumulative effect on increasing soil moisture, extending periods of wet soil and hence promoting grass growth. However, the response of grass NDVI to different precipitation intensity varies spatially. In some pixels of northwest of NW, the correlation values between light precipitation and grass NDVI are higher than those between heavy or moderate precipitation and grass NDVI, which indicated that light precipitation has stronger impact than moderate or heavy precipitation. The reason is that annual total precipitation in the region was mostly less than 150 mm and heavy precipitation is rare [61], but same threshold values (compared to the entire RAA) for defining precipitation intensity levels were used.

Table 2. The composition and frequency of different intensity precipitation in annual total precipitation in relative humid areas (RHA) and relative arid areas (RAA) respectively. Composition indicates that precipitation total quantity (mm) in one year and frequency indicates that the number of precipitation events in one year for each precipitation intensity. These statistics were based on daily field measurements from weather stations with 164 stations in relative humid areas and 107 stations in relative arid areas.

		RH	IA		RAA				
Intensity	Composition		Frequency		Composition		Frequency		
	Quantity	Percentage	Number	Percentage	Quantity	Percentage	Number	Percentage	
Light	187.7	46.3%	139.3	87%	107.9	39.9%	102.8	86.2%	
Moderate	112.4	27.8%	14.8	9%	62.5	23.1%	10	8.4%	
Heavy	104.8	25.9%	6	3.7%	100	37%	6.4	5.4%	

Precipitation excluding or enhancement experiments have shown that variations of precipitation intensity significantly altered the grass growth and production [2,62]. In fact, changes in precipitation also show large variations in different regions, with respect to precipitation amount, frequency or intensity. Both historical and projected climate data show that extreme weather including the increase in heavy precipitation will become more frequent in the next decades [63–65]. In our study, the increase of heavy precipitation was not significant, due to the limited length of the study period, whereas a significant increasing trend was found when the period was extended to the 1960s (Figure S1). Effects of precipitation on vegetation are exerted in the form of charging soil water which is normally deducted by surface runoff, soil and canopy evaporations. Changes in different features (frequency, intensity or both) of precipitation may lead to substantially different effects on grasslands. The 5th IPCC report [66] projects an increase in heavy precipitation events in northern China, and our study shows that grass NDVI is more sensitive to heavy precipitation than light or moderate precipitation, implying positive effects on grasslands, particularly on those arid or semi-arid grasslands.

However, northern China is an environmentally fragile region, especially in the northwestern part. Soil erosion is becoming more and more serious, resulting from reclamation of natural vegetation areas. Heavy precipitation is considered as an important factor to trigger soil erosion, particularly from

July to September, when a sharp reduction in vegetation coverage occurs after wheat harvesting [67]. Therefore, only appropriate land-use shifts from agricultural lands to natural vegetation lands can ensure that vegetation in northern China benefits from more heavy precipitation events in the future.

4.3. Outlook and Uncertainties in the Study

In this study, we investigated the effects of precipitation and growing season temperature on grassland NDVI in northern China. The results showed that heavy precipitation had stronger influence on grass NDVI than moderate and light precipitation. However, different levels of temperature are expected to have different effects on grass growth, particularly for extremely hot and cold temperature. For example, extreme heat waves have widely caused productivity reduction in Europe [68,69]. In North America, the cooling trend of spring temperature caused NDVI decreased obviously [24]. With the increasing trend of extreme days in northern China [59], more efforts should be focused on the response of vegetation to different levels of temperature as well. Besides, biological aspects in both the timing of precipitation event and their regularities could also play vital roles in influencing vegetation growth. Water demand for vegetation growth in summer is much larger than in spring or autumn [28], and summer drought has caused significant decrease in NDVI in inner Asia [16].

Other factors, including grazing activities and the accuracy of interpolated spatial climate data, may distort the responses of NDVI to changes in precipitation and temperature. Grazing was typically to decrease the aboveground biomass of grasslands but may also promote grass regrowth in some cases [70]. The area with strong grazing activities accounts for only 10%–20% of grasslands in our study region [71], so we assume that grazing will not significantly impact the result of our analysis. Inaccuracy of interpolated climatic data can also be an important source of bias of the results. We quantified uncertainty between interpolated data and observed values, showing that relative errors of interpolation vary from 7% to 21% for annual precipitation, and from 5% to 18% for annual temperature. Finally, spatial resolution of remote sensing dataset may also influence the response of NDVI to climate. Coarse remote sensing data are able to reveal changes in vegetation cover and yield comparable results regarding the temporal trends and spatial patterns compared with fine resolution data [72,73]. Fine resolution data indeed provides additional information to identify vegetation changes. However, disadvantages, both large data storage and long time required for image processing may prohibit its application in large regions [74].

In addition, many other vegetation indices (VIs) can be used for researching vegetation changes in response to climate change. NDVI is one of the most widely used indices, as it enables the elimination of topographic effects and variations in the sun illumination angle, as well as other atmospheric elements such as haze [11]. As well known, NDVI is easily saturated in densely vegetated regions, indicating that derived signals are of high uncertainties [75,76]. Some other VIs, such as enhanced vegetation index (EVI) [11], soil adjusted vegetation index (SAVI) [77], and atmospherically resistant vegetation index (ARVI) [78], may reveal more in understanding the response of grass NDVI to different levels of precipitation and temperature. Applications of these VIs into grassland ecosystems in response to change in climate, and inter-comparisons between different VIs (including NDVI), should be emphasized in future researches.

5. Conclusions

A long time series of GIMMS NDVI dataset was used to correlate with precipitation intensity and temperature in northern China. Growing season NDVI significantly increased at a rate of 0.0005 year⁻¹ during the period from 1982 to 2011 and precipitation, to a great extent, could reflect the changes in NDVI in relative arid areas. Changes in grassland NDVI were more sensitive to heavy precipitation than light and moderate precipitation. The sensitivities of changes in grassland NDVI to heavy precipitation were 0.37 and 0.19 in relative arid areas and relative humid areas, respectively, which were very close to the sensitivities to total precipitation. We concluded that changes in grassland NDVI were strongly impacted by heavy precipitation in 56% of northern China, but temperature played a comparable role to precipitation in relative humid areas. In high altitude areas, temperature was the main limiting factor for grass NDVI rather than precipitation.

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Author Contributions

Longhui Li designed the study. Xiuliang Yuan processed the data. Xi Chen and Hao Shi gave comments and suggestions on the manuscript. All authors interpreted the results and wrote the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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