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ORIGINAL PAPER

# Soil moisture outweighs temperature for triggering the green-up date in temperate grasslands

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**Abstract**
Investigating grassland phenology and its relationship with climatic factors is crucial for understanding ecosystem responses to climate change. However, there have been few studies on the impact of soil moisture on grassland phenology. In this study, we extracted the green-up date in the Inner Mongolia grasslands, China, using the normalized difference vegetation index (NDVI) data from the Global Inventory Modeling and Mapping Studies (GIMMS) NDVI3g dataset (1982–2015) and the Moderate Resolution Imaging Spectroradiometer (2001–2015). We investigated the spatiotemporal pattern of the green-up date and its relationship with four climatic factors, including growing degree days, chilling days, soil moisture, and solar radiation. Most areas (67.1%) exhibited a trend towards earlier green-up date, but the significant trends ($p < 0.05$) were only found in 13.4% of the areas. For both datasets, the pixels with a negative regression coefficient of soil moisture accounted for more than 87% of the total area (more than 21% significantly, $p < 0.05$). Regarding the other factors, the sign of regression coefficients was not consistent among pixels. Thus, soil moisture correlated more significantly with the green-up date in temperate grasslands compared with the other climatic factors. This study provides the scientific basis for better understanding the mechanism of phenological response to climate change in temperate grasslands.

## 1 Introduction

Plant phenology is the study of recurring events in plants during their growth and development life cycle, such as the date of bud-burst, flowering, and leaf coloring. Phenology regulates many hydrological processes, such as evapotranspiration and runoff (Obrist et al. 2003; Senay 2008). In addition, phenological changes alter the biomass production, which in turn affects the terrestrial carbon cycle (Forkel et al. 2016). The differences in phenological changes among species may influence the community structure by causing phenological mismatches between predators and prey or pollinators and plants (Kharouba et al. 2018). Thus, investigating the driving factors of phenological phases improves our understanding of ecosystem responses to climate change.

Grassland is one of the most widespread vegetation types in the world (Chen et al. 2014), which occupies about 30% of the earth's ice-free areas (Gao et al. 2016). The carbon stocks of grassland soil amount to at least 10% of the global total (Dixon et al. 2014). Over the past several decades, the climate of the grassland ecosystem has changed significantly. The temperature in the Great Plains, which is the most recognizable grassland ecosystem in North America (Dixon et al. 2014), increased significantly, but the precipitation decreased slightly, from 1982 to 2009 (Tang and Leng 2013). In Inner Mongolia grasslands of China, the warming rate (0.37 °C/decade) was much higher than the global warming rate (0.14 °C/decade), and the mean annual precipitation in 46 meteorological stations decreased by 1.63 mm/decade, from 1961 to 2012 (Hu et al. 2015). Such climate changes have altered the phenological phases of the grassland ecosystem. For example, the spring phenology of herbaceous plants in China advanced by 0.57 days/year during the period from 1960 to 2011 (Ge et al. 2015). Furthermore, many studies have investigated the driving factors of phenological changes at the species level for a few grassland ecosystem locations. For example, one study

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found that the advance in dates of first leaf unfolding of a widely distributed herbaceous species, *Taraxacum mongolicum*, was mainly driven by a temperature increase (Chen et al. 2015). The increased precipitation in January and December, falling mainly as snow, leads to later flowering of wildflowers in the semi-arid grasslands of the Northern Rocky Mountains (Lesica and Kittelson 2010). Thus, the phenophases of herbaceous plants are governed by multiple climatic factors.

Compared with the conventional ground observation method, remote sensing is a more useful tool for studying the terrestrial vegetation at a regional and a global scale (Running et al. 1994; DeFries 2008). Land surface phenology is defined as the study of the spatiotemporal development of a vegetated land surface that is revealed using synoptic spaceborne sensors, and it is an important biophysical application of satellite remote sensing (White et al. 2009). Using remote sensing data, an overall advancing trend of the green-up date at the landscape level was found in the grasslands of the Mongolian Plateau (Miao et al. 2017) and the Tibetan Plateau (Shen et al. 2015a). The studies based on the remote sensing data also suggested that the earlier green-up date of the grasslands was primarily triggered by temperature and precipitation (Wang et al. 2015; Shen et al. 2015b; Ren et al. 2018). For example, the green-up date in Inner Mongolia grasslands was significantly and negatively correlated with precipitation and temperature in most places (Ren et al. 2018). Especially, in more arid areas, the precipitation presented an even stronger correlation with the spring phenology (Cong et al. 2013; Zhu and Meng 2015). Compared with precipitation, soil moisture was a more straightforward index affecting grassland phenology, because it directly reflects the available water for plant seeds and roots (Yuan et al. 2007; Liu et al. 2013). The soil moisture also mediated the phenological response of grass to warming in a semi-arid grassland (Zelikova et al. 2015).

However, to date, due to the lack of reliable regional soil moisture data, only a few studies have focused on the impact of soil moisture on grassland phenology retrieved from satellite observations. Recently, active and passive microwave sensors were used for the retrieval of near-surface soil moisture data (Kerr et al. 2001; Liu et al. 2012; Dorigo et al. 2017). By combining the long-term and consistent soil moisture time series and remote sensing methods for extracting vegetation phenology, we were able to comprehensively explore the response of grassland phenology to water availability on a large scale. We selected Inner Mongolia, the main distribution area of temperate grassland in Asia, as the study area to retrieve green-up dates based on the remote sensing data. In order to compare the impact of soil moisture with other climatic factors, temperature and solar radiation were also considered in this study. Our purpose was to reveal the temporal-spatial pattern of spring green-up dates for different grassland types in Inner Mongolia from 1982 to 2015, and to explore the relative importance of climatic factors that trigger the green-up date in grasslands.

## 2 Materials and methods

### 2.1 Study area

Inner Mongolia (IM) lies in the north of China (Fig. 1a), with an average elevation of about 1000 m (Fig. 1b). It is mainly dominated by a temperate continental monsoon climate. The annual total precipitation is greater than 450 mm in the east, and less than 10 mm in the west. The vegetation types were identified by a digitized 1:1000000 vegetation map of China (Zhang 2007). From east to west, the main vegetation types are meadow steppe, typical steppe, and desert steppe (Fig. 1c). Meadow steppe, which is distributed primarily in the eastern steppe zones, is a transitional type between steppe and forest. Meadow steppe thrives in a semihumid climate, where annual precipitation is 350–550 mm. The plant community is composed of *Aneurolepidium chinensis*, *Stipa baicalensis*, other xeric gramineous plants, and forbs. Typical steppe (dry steppe) is found mostly on the central Inner Mongolia plateau and at low to middle elevation in the western desert mountains. The annual precipitation in these areas is 200–350 mm. The plant community consists primarily of xeric gramineous plants. Desert steppe, which is distributed to the west of the typical steppe and below the mountain steppe, is a transitional type between steppe and desert. Annual precipitation in the desert steppe is 150–250 mm. The plant community consists mostly of small, extremely xeric *Stipa* spp., accompanied by subshrub or shrub (National Research Council 1992).

### 2.2 Datasets

Two remote sensing datasets were used to extract the green-up date over grasslands of Inner Mongolia. The first dataset was the Global Inventory Modeling and Mapping Studies (GIMMS) NDVI3g data (1982–2015). This dataset included the global normalized difference vegetation index (NDVI) with a temporal resolution of 15 days and spatial resolution of 1/12°gerenated from NOAA/AVHRR sensors (Pinzon and Tucker 2014), which could be downloaded from the website of the National Center for Atmospheric Research (https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/). The second dataset was a 16-day composite MODIS product MOD13C1 from 2001 to

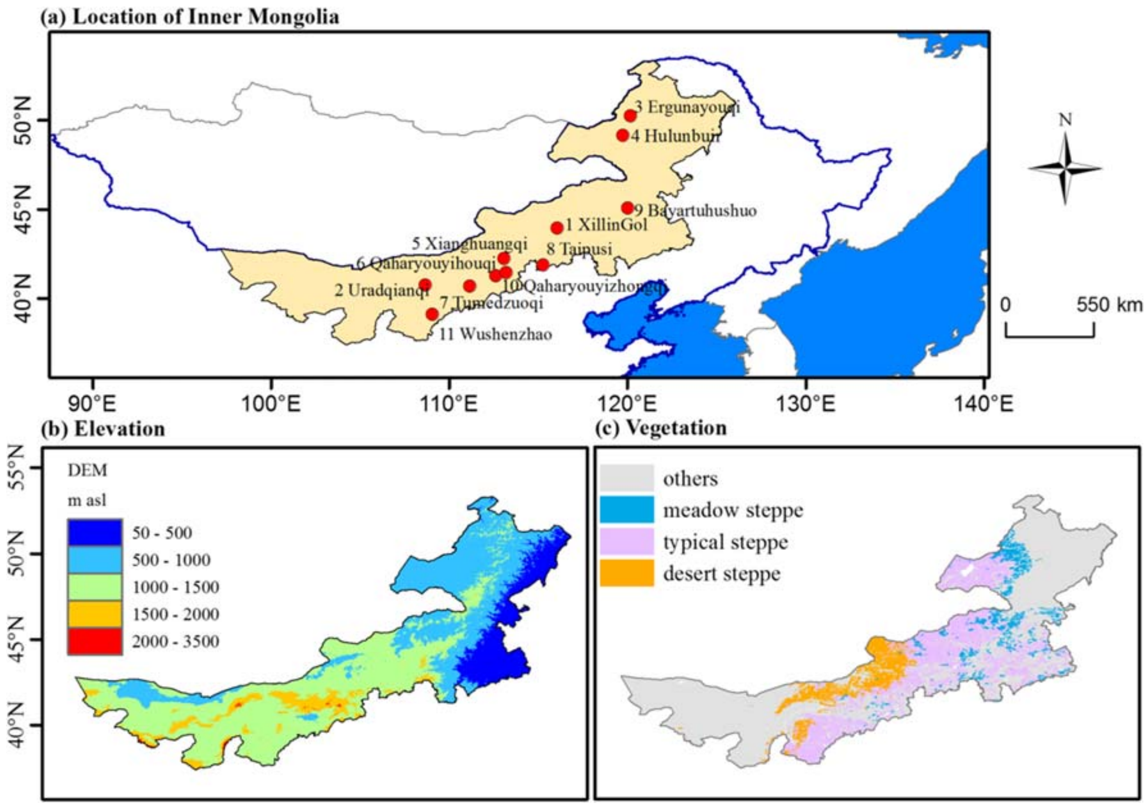



**Fig. 1** The location, elevation, and vegetation types of Inner Mongolia, China. **a** Location of Inner Mongolia and the in situ phenological observation stations; **b** the elevation of the study area; **c** vegetation types of the study area

2015, which was derived from Level-1 and Atmosphere Archive and Distribution System (LAADS) of the Distributed Active Archive Center (DAAC). The MODIS NDVI data has a temporal resolution of 16 days and a spatial resolution of 1/20°. The ground-observed phenological data were used to validate the remote sensing–based green-up date. We derived the observation data of the leaf unfolding date (LUD) of the dominant herbaceous plants at 11 stations from 1982 to 2012 at the National Meteorological Information Center of China (Table 1). In total, 44 LUD time series of 15 herbaceous plants were investigated. The observation records in all the stations and years were compared with the green-up date of corresponding pixels in the remote sensing data

The meteorological data, including daily near-surface mean temperature and downward shortwave radiation, were obtained from the China Meteorological Forcing dataset (He and Yang 2011). It covered the period from 1979 to 2015 with the temporal and spatial resolution of 3 h and 0.1°, respectively. The soil moisture data we used (CCI SM v04.2) was the most complete and consistent global soil moisture data record based on active and passive microwave sensors, which was downloaded from the website of the European Space Agency (http://www.esa-soilmoisture-cci.org). The dataset was accurate for estimating soil moisture in the steppe regions of China (An et al. 2016). It consists daily soil volume water content at a depth of 20–100 cm from 1978 to 2015 at a resolution of 0.25 × 0.25° (Liu et al. 2012). Due to the different spatial resolution of remote sensing data and meteorological data, the nearest-neighbor method was used to interpolate the meteorological data to make its spatial

**Table 1** Summary of species investigated in this study. The station number corresponds to the number shown in Fig. 1a

| Number | Species | Stations with the phenological data |
|---|---|---|
| 1 | *Taraxacum officinale* | 1, 2, 3, 4, 5, 6, 7, 8, 9 |
| 2 | *Plantago asiatica* | 1, 2, 3, 4, 5, 6, 7, 8, 9 |
| 3 | *Iris ensata* | 1, 3, 4, 6, 7, 8, 9 |
| 4 | *Xanthium sibiricum* | 1, 2, 8, 9 |
| 5 | *Sonchus oleraceus* | 2, 4, 7, 8 |
| 6 | *Chenopodium glaucum* | 1 |
| 7 | *Carex duriuscula* | 9 |
| 8 | *Artemisia argyi* | 8, 9 |
| 9 | *Iris tenuifolia* | 1 |
| 10 | *Leymus chinensis* | 6 |
| 11 | *Draba nemorosa* | 6 |
| 12 | *Achnatherum splendens* | 6 |
| 13 | *Festuca ovina* | 6 |
| 14 | *Stipa baicalensis* | 10 |
| 15 | *Phragmites australis* | 11 |

resolution consistent with that of GIMMS or MODIS data (Karlsson and Yakowitz 1987).

## 2.3 Methods

### 2.3.1 Extraction of spring phenology from satellite data

For areas with sparse vegetation, the vegetation index mainly reflected the background information of soil. Therefore, areas with annual mean NDVI < 0.1 were removed first (Shen et al. 2014). In this study, about half pixels of the desert steppe was removed. In order to solve the contamination caused by clouds and snowmelt, Savitzky-Golay filtering was applied to smooth the NDVI time series (Chen et al. 2004). Subsequently, the NDVI time series was fitted year by year with the following double logistic function (Elmore et al. 2012).

$$\mathrm{VI}(t) = a_1 + (a_2 - a_7 t)\left[\frac{1}{1+e^{(a_3-t)/a_4}} - \frac{1}{1+e^{(a_5-t)/a_6}}\right] \qquad (1)$$

where VI($t$) was the NDVI value at day of the year $t$. $a_1$–$a_7$ were parameters, which were fitted using Levenberg-Marquardt least-squares method. The Levenberg-Marquardt algorithm (LMA) is used to solve non-linear least squares problems. In many cases, it can obtain a solution even if it starts very far off the final minimum. Thus, the LMA is more robust than conventional methods, such as the Gauss-Newton algorithm (Kanzow et al. 2004). The green-up date was defined as the date when the first local maximum value of the first derivate of the VI time series occurs (Studer et al. 2007) (Fig. S1).

The trend in the green-up date was estimated using a linear regression between the green-up date and year for each pixel. The $t$-test was used to test the significance of the linear trends.

### 2.3.2 Identification of climatic factors influencing spring phenology

According to previous studies (Liu et al. 2013; Huang et al. 2019), four major climatic factors were considered to have a potential influence on the green-up date in grasslands. Because the green-up date of the plants is a phenological event that occurred annually, for each year, we need to calculate the mean value of potential climate factors in the most relevant period influencing plant phenology.

1. The growing degree days (GDD), calculated as the accumulated temperatures higher than 0 °C from 1 January to the multiyear mean green-up date during 1982–2015 for the GIMMS data and 2001–2015 for the MODIS data (Cong et al. 2017).
2. The chilling days (CD), defined as the number of days when the temperature is below 0 °C from 1 October of the previous year to the multiyear mean green-up date (Cong et al. 2017).
3. The soil moisture (SM), which is the mean soil volume water content from 1 April to the multiyear mean green-up date. We chose 1 April as the start date because, in this region, the soil was freezing before April (Zhao et al. 2016).
4. The solar radiation (INS), computed as the mean downward short-wave radiation from 1 January to the multiyear mean green-up date. We assumed that solar radiation affects the surface physical processes and thus affects dormancy release of the belowground buds of perennial herbs. Therefore, we chose 1 January as the start date when the buds of perennial herbs were still dormant.

For each pixel, the climatic factors were calculated yearly, and a multiple regression model was performed between the time series of the green-up date and all potential climatic factors for each pixel. The equation of the multiple regression model was:

$$y = b_0 + b_1\mathrm{GDD} + b_2\mathrm{CD} + b_3\mathrm{SM} + b_4\mathrm{INS} \qquad (2)$$

where, $y$ is the green-up date; GDD, CD, SM, and INS represent the above climatic factors; $b_1$–$b_4$ are the regression coefficients of each factor; and $b_0$ is the intercept. The goodness-of-fit ($R^2$) of the regression model was calculated, and the $F$-test was used to test the overall significance of the multiple linear regression models. Furthermore, the regression coefficient reflected to what extent each factor impacted the spring phenology. The sign (negative or positive) of the regression coefficient reflected the direction of the influence of different climatic factors on spring phenology (advance or delay). The $t$-test was used to test whether the regression coefficients were significantly different from zero. Through the frequency statistics of the regression coefficients across all pixels, we identified whether the influence of climatic factors on the green-up date was consistent among different pixels. In consideration of the multicollinearity of different climate factors, we also used partial correlation analysis method to analyze the influence of the four climatic factors on the green-up date. The results are shown in the supplementary material (Fig. S2).

## 3 Results

### 3.1 Spatial pattern of the green-up dates

The green-up dates in grasslands derived from the GIMMS and MODIS data showed a similar spatial pattern (Fig. 2). The earliest green-up date was found in the north-central region. In these areas, the earliest green-up date occurred at the mid of March (day of year 80) and at the beginning of April (day of

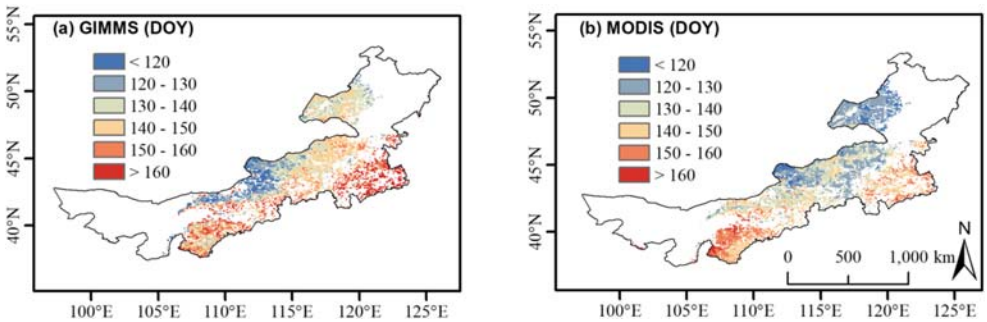



**Fig. 2** The spatial pattern of green-up dates in Inner Mongolia grasslands averaged from 2001 to 2015. **a** GIMMS data and **b** MODIS data. DOY, day of the year

year 100) for the GIMMS and the MODIS data, respectively. The latest green-up date, which was found in southeast and southwest areas, occurred at the end of June for both datasets. In general, the spatial variance in the green-up dates derived from the MODIS data (standard deviation, 12.39 days) was larger than that from the GIMMS data (standard deviation, 10.31 days) (Fig. 2).

We also compared the green-up dates in different steppe types (Fig. 3). The results showed that the mean green-up dates in the typical steppe were later than the meadow steppe for both datasets. However, the desert steppe showed the earliest green-up dates in the GIMMS data, but the green-up dates in desert steppe became relatively later than the meadow steppe for the MODIS data.

### 3.2 Temporal variations of the green-up dates

The interannual variations in the mean green-up date from 1982 to 2015 are shown in Fig. 4. We found that the green-up dates derived from the two datasets showed good consistency from 2001 to 2009. However, from 2010 to 2015, although the fluctuation was generally consistent, the green-up dates from the MODIS data were earlier than that from the GIMMS data. Regarding the linear trend, the green-up dates in the Inner Mongolia grasslands from the GIMMS data exhibited an advancing trend of − 0.10 days/year in recent 34 years (not significant at $p < 0.05$). The advancing trend of the green-up dates from the MODIS data was larger (− 0.73 days/year) than the GIMMS data from 2001 to 2015; however, it was still not statistically significant.

Figure 5 shows the spatial distribution of the spring phenological trend in Inner Mongolia. From 1982 to 2015, the green-up dates were delayed mainly in the southern areas, and the delaying trend was most evident in the southern Ordos (Fig. 5a). The areas with significantly advancing trends were mainly located in the western Hulunbuir and northern Xilingol. From 2001 to 2015, the trend of green-up dates showed a similar pattern between the GIMMS and the MODIS data, but the number of pixels showing an advancing green-up date of the GIMMS data was larger than that of the MODIS data. For the MODIS data, the areas with an earlier green-up date were majorly located in the southeast of Tongliao city, while the areas with a delayed green-up date were mainly located in the new Barag right banner of Hulunbuir.

We further investigated the frequency distribution of the green-up date trends in different steppe types (Fig. 6). From 1982 to 2015 (GIMMS data), in the typical steppe, the earlier green-up date accounted for 68.9% of the pixels (15.9% significantly at $p < 0.05$). Significant delayed trends occurred in only 6.7% of the pixels. The mean trend in the typical steppe was largest among the three steppe types (− 0.21 days/year). Regarding the meadow steppe, 72.6% of the pixels showed a trend towards earlier green-up (16.1% significantly at $p < 0.05$), while 27.4% of the pixels showed a trend towards later green-up (6.2% significantly). The mean trend of meadow steppe was − 0.13 days/year. The green-up dates in desert steppe became earlier in 56.8% of the pixels (0.6% significantly) and delayed in 43.2% of the pixels (4.0% significantly), with a mean trend of − 0.12 days/year.

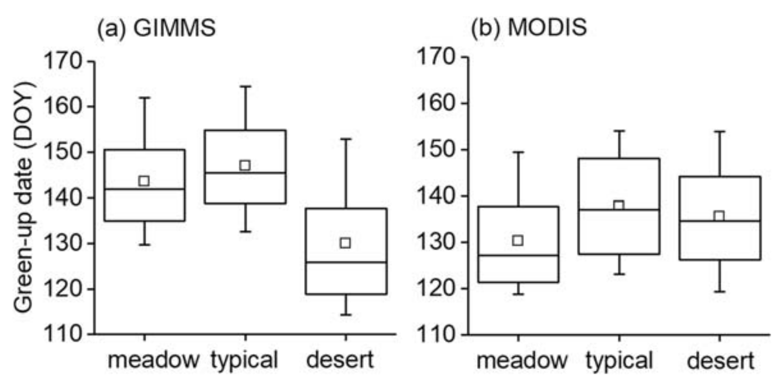



**Fig. 3** The distribution of green-up dates for the different steppe types. **a** GIMMS data and **b** MODIS data. The bottoms and tops of the boxes are the 25th and 75th percentiles, respectively. The ends of the whiskers are the 5th and 95th percentiles, respectively. The bands and squares in the boxes show the median and mean values, respectively

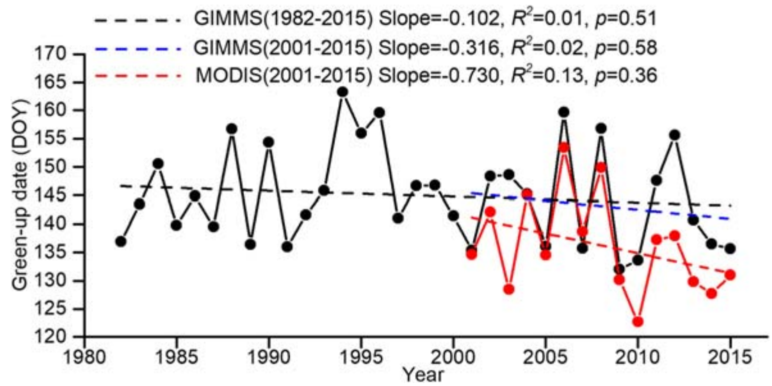



**Fig. 4** The interannual variation of the mean green-up dates in Inner Mongolia grasslands. The dashed lines show the linear regression lines

The MODIS data reflected the phenological trends in the recent 15 years (Fig. 6, right column). In the meadow steppe, the mean trend of the green-up date was − 0.76 days/year. The earlier green-up date appeared in 92.6% of the pixels (28.3% significantly). Regarding the typical steppe, the mean trend of the green-up date was − 0.58 days/year, and the green-up date became earlier (12.2% significantly) in 79.5% of the total area. In the desert steppe, the pixels with earlier green-up dates accounted for 78.9% of the total area (6.3% significantly at $p < 0.05$). The mean trend of green-up dates in desert steppe was strongest (− 1.12 days/year).

The trend of the green-up dates in different steppe types presented similar patterns along the latitudinal and elevational gradients from 1982 to 2015 (Fig. 7). The trend towards a later green-up date was found at the lower latitude and lower elevation, and the trend towards an

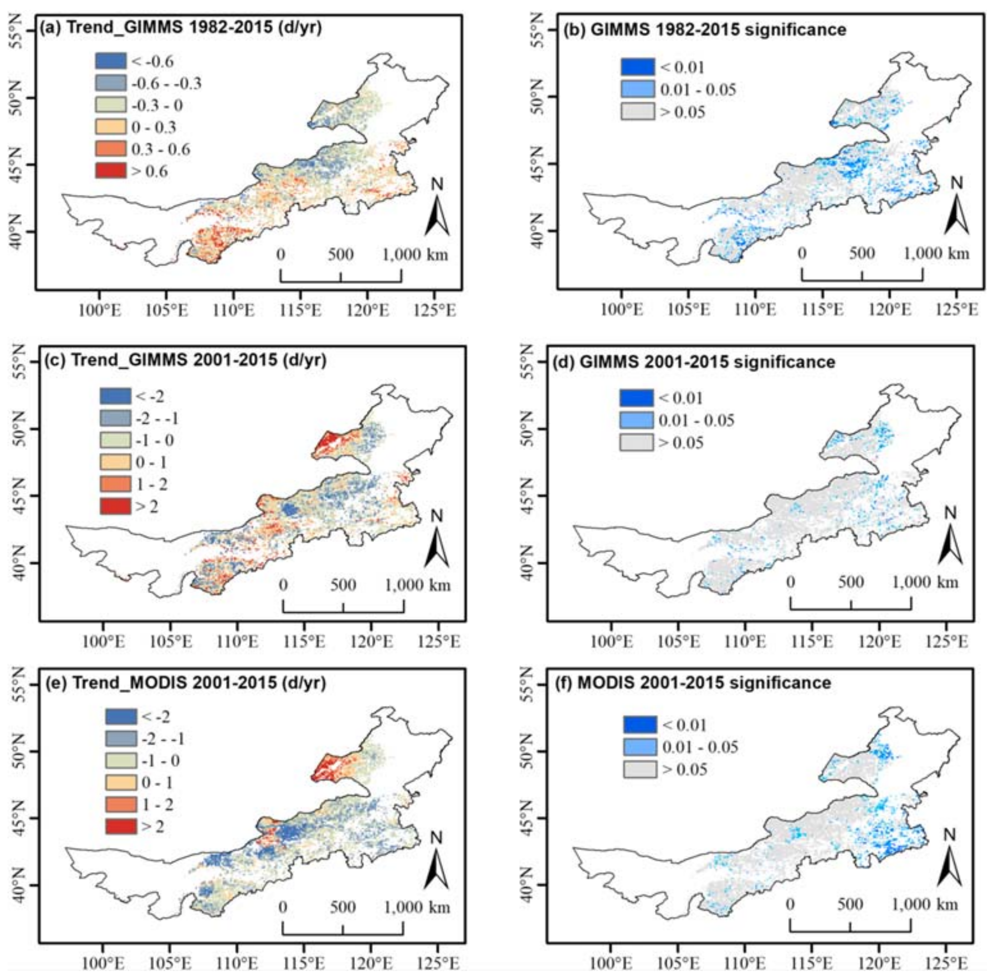
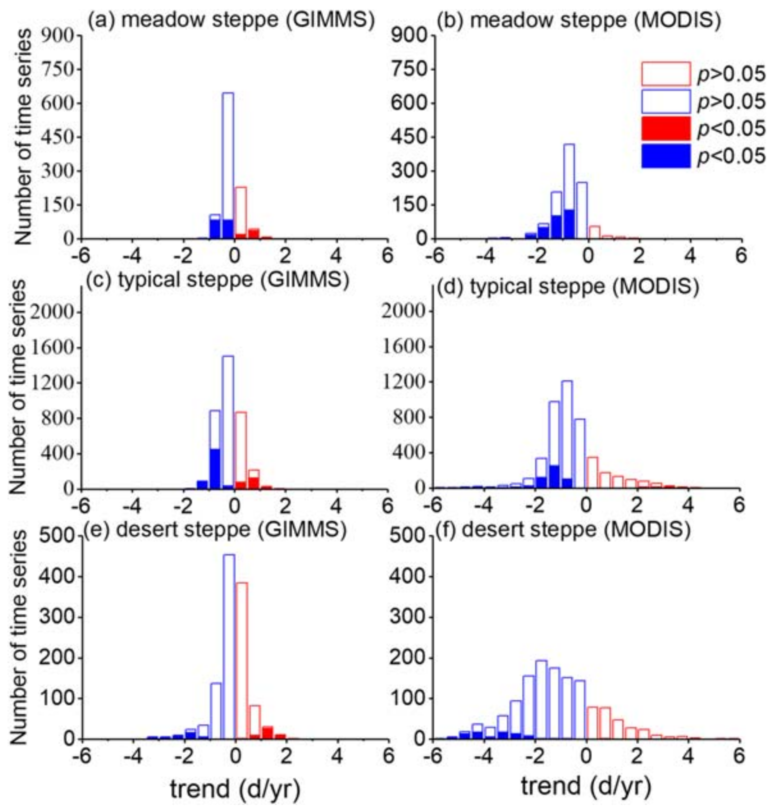



**Fig. 5** Spatial distributions of the green-up date trends for grassland in Inner Mongolia. **a**, **b** Trends and $p$ values for the GIMMS data (1982–2015); **c**, **d** trends and $p$-values for the GIMMS data (2001–2015); **e**, **f** trends and $p$-values for the MODIS data (2001–2015). The positive trends indicate later green-up dates, and negative trends indicate earlier green-up dates. The unit d/yr refers to days/year

**Fig. 6** Frequency distribution of the trends in the green-up dates in different steppe types. The trends for the GIMMS data (1982–2015) and the MODIS data (2001–2015) are shown. The positive trends indicate later green-up dates, and negative trends indicate earlier green-up dates

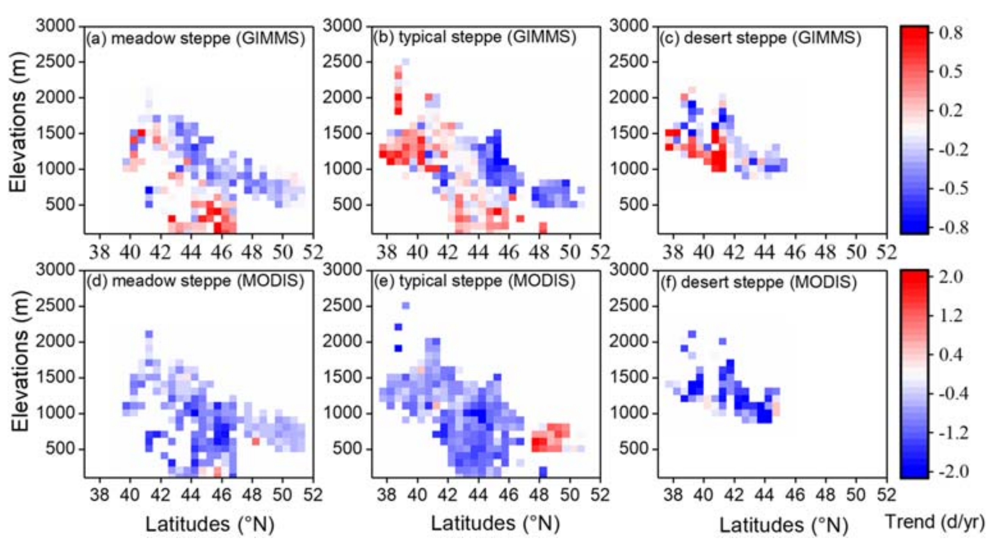



earlier green-up date was found at the relative higher latitude and higher elevation. From 2001 to 2015, the earlier trend of green-up dates in meadow steppe was stronger at the lower latitude and lower elevation (Fig. 7d). Regarding the typical steppe, the delaying trend was only found in higher latitude areas (Fig. 7e). For desert steppe, there was no obvious pattern in the trend of green-up dates along latitudinal and elevational gradients (Fig. 7f).

### 3.3 Relationship between the green-up date and climatic factors

A multiple linear regression model was applied to study the relationship between the GIMMS-based green-up dates and the climatic factors in each pixel (Fig. 8, first row). The model, on average, explained 18.28% of the variations of the green-up dates. In 17.6% of the pixels, the $p$ value for the $F$-test of

**Fig. 7** The variation in the linear trend of the green-up dates with latitudinal and elevational gradients in meadow steppe (a and d), typical steppe (b and e), and desert steppe (c and f). The first and second rows show the trends derived from the GIMMS data (1982–2015) and the MODIS data (2001–2015), respectively



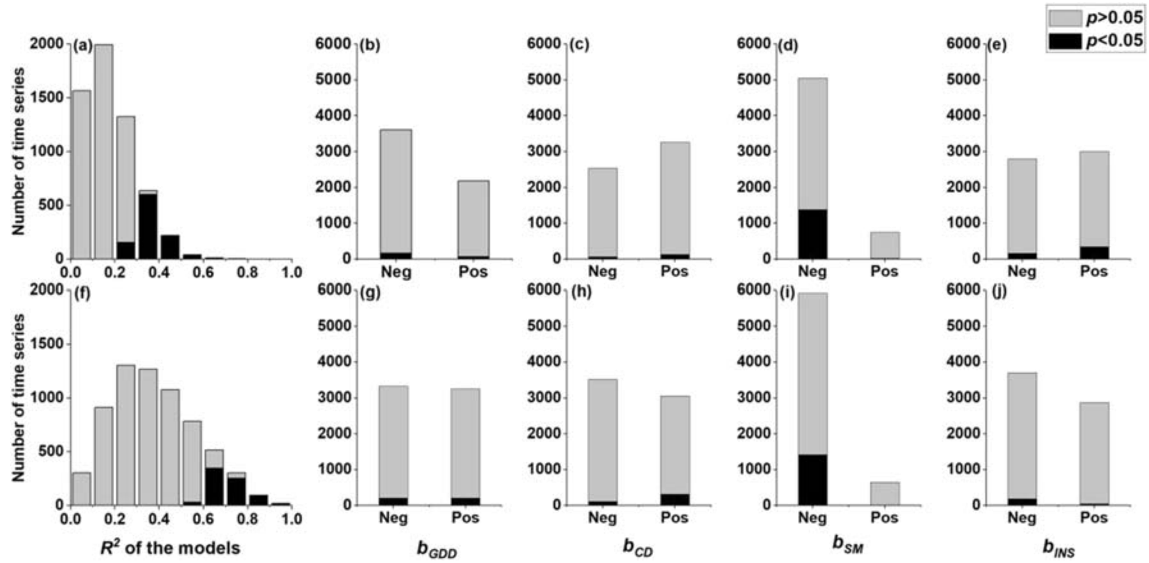



**Fig. 8** The results of the multiple linear regression model between green-up dates and different climatic factors. The first row shows the results of the GIMMS data, and the second row shows the results of the MODIS data. The first column shows the $R^2$ of the models. The black in the first column shows the number of models that reach a significant level of 0.05 by $F$-test. The second to the fifth column shows the regression coefficient of growing degree days ($b_{\mathrm{GDD}}$), chilling days ($b_{\mathrm{CD}}$), soil moisture ($b_{\mathrm{SM}}$), and insolation ($b_{\mathrm{INS}}$). The black in these columns shows the number of regression coefficients that are significantly different with zero ($p < 0.05$). Neg and Pos indicate negative and positive regression coefficients, respectively

the overall significance was less than 0.05, which indicated that the multiple regression model which considered four climatic factors effectively simulated the spring phenological change for about one-sixth of the total pixels. Concerning the MODIS-based green-up dates (2001–2015), the model including four climatic factors explained 37.96% of the variations on average. However, significant $F$-test results of the regression models were only found in 11.3% of the total pixels.

For the GIMMS data, soil moisture had almost a consistently negative effect on the green-up dates. The pixels with a negative regression coefficient of soil moisture accounted for 87.2% of the total area, with 23.9% significantly ($p < 0.05$). On the contrary, the signs of regression coefficients for the other three factors were less consistent. For example, the negative regression coefficients of GDD, chilling days, and insolation were found in 62.3%, 43.8%, and 48.2% of the total pixels, respectively. For the MODIS data, the regression coefficients of soil moisture were negative for 90.0% of the total pixels (21.6% significantly). For the other factors, the regression coefficients were negative in about half of the total pixels, and positive in the remaining pixels. The number of pixels exhibiting significant correlations between green-up dates and soil moisture was greater than the other climatic factors.

According to the previous analysis, soil moisture was an important factor influencing the green-up date in grasslands. Therefore, the regression coefficient of the green-up date against soil moisture, which reflects the sensitivity of green-up date to soil moisture, was investigated (Fig. 9). The result from the GIMMS data showed that the strongest sensitivity of green-up date to soil moisture was located in the central and western Hulunbuir region, where every 1% $m^3/m^3$ increase in soil moisture led to a green-up date that was 3 to 6 days earlier. In south-central Xilingol, the sensitivity even exceeded 6 days/1% $m^3/m^3$ in a few pixels. For the MODIS data, the sensitivity was most significant in the southern Wushenzhao region, which reached 3 to 6 days/1% $m^3/m^3$.

## 4 Discussion

In this study, we used two remote sensing datasets (GIMMS and MODIS) to extract the green-up date in Inner Mongolia temperate grassland. The retrieved green-up date of grassland was compared with the LUD of herbaceous plants at corresponding stations (Fig. S3). We noticed that for both datasets, the green-up dates retrieved from the GIMMS and MODIS data were later than the LUD of herbaceous plants observed on the ground in the corresponding pixel. The $R^2$ between GIMMS-based green-up date and LUD (0.18) was slightly larger than that between MODIS-based green-up date and LUD (0.14), which suggested that the GIMMS dataset was slightly better to be used to retrieve green-up dates. However, the retrieved green-up date from GIMMS and MODIS data showed relatively good consistency with the $R^2$ of 0.30 (Fig. S3c). Therefore, the MODIS and GIMMS produced similar green-up date. The advantages of MODIS data was that its spatial resolution (500 m) is higher than GIMMS data (8 km) and could capture more detailed spatial difference among vegetation types. The mismatch between ground-

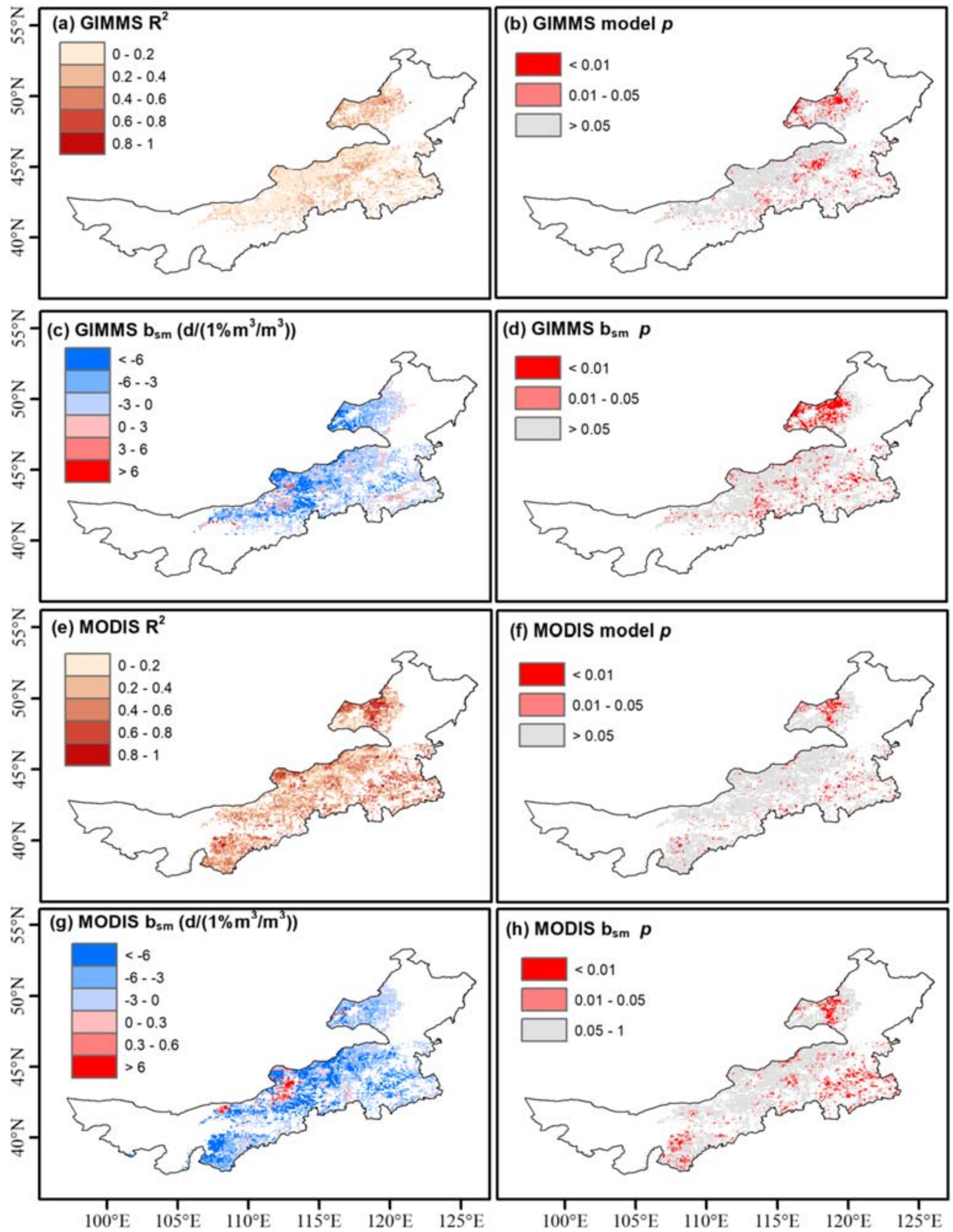



**Fig. 9** The spatial pattern of the explained variance ($R^2$) and the overall significance ($p$ value) of the multiple regression model. **a** The goodness of fit ($R^2$) for the GIMMS data, **b** the overall significance ($p$ value) for the GIMMS data, **c** the regression coefficient of soil moisture ($b_{sm}$) for the GIMMS data, **d** the significance of $b_{sm}$ for the GIMMS data, **e** the $R^2$ for the MODIS data, **f** the overall significance ($p$ value) for the MODIS data, **g** the $b_{sm}$ for the MODIS data, and **h** the significance of $b_{sm}$ for the MODIS data

based and satellite-derived spring phenology could be attributed to their difference in ecological definitions (Fisher and Mustard 2007; Wang et al. 2014). The satellite-derived green-up date reflected the date when the pixel-based vegetation index reached a particular level. The pixel-based vegetation index depended on the state of development of various ecological communities, which occupied different percentages of the area in a particular pixel (Liang et al. 2011). On the contrary, the ground-observed spring phenology referred to a specific growth stage of an individual, such as leaf-out and flowering.

At the landscape level, the green-up dates in grassland became earlier during the 30-year period (1982–2015) and the 15-year period (2001–2015), although the significant trend was only found in parts of pixels. To compare this result with other studies, we summarized the results of seven previous studies which focused on the temporal-spatial change of spring phenology in Inner Mongolia based on the remote sensing data (Table 2). These studies used the MODIS, AVHRR, or SPOT data from the 1980s to the 2000s. Furthermore, the methods for the reconstruction of the vegetation index and determination of the green-up dates were quite different. Consistent with our results, all these studies demonstrated an overall advancing trend of spring green-up dates in the Inner Mongolia grasslands.

**Table 2** Previously reported changes in vegetation phenology from different resources in Inner Mongolia (IM)

| Data sources | Curve approaches | Determination approaches of phenophases | Period | Region | Trends (days/decade) | References |
|---|---|---|---|---|---|---|
| AVHRR NDVI | Polynomial fitting | Maximum relative change | 1982–1999 | Temperate grassland in China | − 6.7 | (Piao et al., 2006) |
| SPOT NDVI | Logistic model | The maxima of curvature | 2001–2010 | Temperate grassland in China | − 3.1 | (Hou et al., 2014) |
| MODIS NDVI | Savitzky-Golay filter | The maxima of the second derivative | 2002–2014 | Grassland in IM | − 4.8 | (Gong et al., 2015) |
| SPOT NDVI | HANTS | The maxima of the first derivative | 1998–2012 | Grassland in IM | − 0.7 | (Sha et al., 2016) |
| MODIS PSRI | Double logistic function | Local maximum changing rate of curvature | 2000–2011 | Grassland in IM | 7.7% advanced significantly, 3.3% delayed significantly | (Ren et al., 2017) |
| GIMMS3g NDVI | Polynomial fitting | Maximum relative change | 1982–2011 | Grassland in Mongolian Plateau | − 1.1 | (Miao et al., 2017) |
| MODIS NDVI | Double logistic function | Local maximum changing rate of curvature | 2000–2016 | Grassland in IM | 2.8% advanced significantly, 0.4% delayed significantly | (Ren et al., 2018) |

Grassland is widely distributed in arid and semi-arid regions. Therefore, water condition is the limiting factor for growth and development of herbaceous plants. Previous studies mainly used precipitation to study the effect of water conditions on the phenology of grasslands or herbaceous plants (Lesica and Kittelson 2010; Shen et al. 2015b; Munson and Long 2017; Ren et al. 2018). Compared with precipitation, soil moisture is a more straightforward factor driving grassland phenology. The result of our study showed that soil moisture was a more important controlling factor of grassland spring phenology than temperature and solar radiation, although there was only a significant relationship in less than one-quarter of the pixels. Higher soil moisture accelerated the green-up of grassland, which was consistent with results from previous studies. For instance, Liu et al. (2013) found that soil moisture–based indices explained the interannual shifts of grassland spring phenology better than precipitation-based indices in Inner Mongolia. The onset of spring and subsequent seasonal patterns of plant growth depended on both soil temperature and soil moisture in a semi-arid steppe in the western Great Plains of the USA (Moore et al. 2015). Similarly, soil moisture influenced the phenology of grasslands both directly (greenness was two to three times greater in wet years than in dry years) and indirectly by mediating the magnitude and direction of warming effects (Zelikova et al. 2015). In the Canadian Prairies, fewer water deficits favored an earlier start date of the growing season (Cui et al. 2017). Therefore, phenological timings of herbaceous plant functional types depended on soil water availability, and customizing parameter sets of vegetation soil moisture was important in the dynamic global vegetation model (Kim et al. 2015). In addition, the sensitivity of spring phenology to soil moisture might be related to local climate conditions. For example, Tao et al. (2017) found that the phenological response of temperate grassland to water availability was much larger in more arid regions during 1982–2012 in northern China. Here, we further analyzed the variation in the sensitivity of spring phenology to soil moisture ($b_{sm}$) along with precipitation and temperature gradients (Fig. S4). The result showed that the $b_{sm}$ in arid regions (mean annual precipitation < 200 mm and mean annual temperature > 2 °C) reached approximately − 6 days/1% m$^3$/m$^3$, which was almost three times stronger than the $b_{sm}$ (about − 2 days/1% m$^3$/m$^3$) in relatively humid regions (mean annual precipitation > 400 mm and mean annual temperature < 2 °C). Therefore, the effect of soil moisture on plant phenology weakened in humid regions, because the limitation of water availability on the onset of green-up date reduced.

Many studies based on remote sensing data found that an increase in temperature accelerated the green-up date in grasslands (Miao et al. 2017; Cheng et al. 2018). In this study, we showed that higher temperatures (larger GDD) lead to an earlier green-up date in only approximately 55% of the temperate steppe areas because when multiple factors were considered simultaneously, soil moisture explained a large number of the changes in grassland phenology, making the effect of temperature less obvious. However, we did not deny that the temperature is a seasonal cue that directly affects growth and development rates of herbaceous plant(Wilczek et al. 2010).

The number of chilling days was also a possible factor affecting the spring phenology of grassland. Studies on woody plants showed that a decrease in the number of chilling days increased the accumulated temperature required for spring bud-burst, thus inhibiting the advance of spring phenology (Laube et al. 2014; Carter et al. 2017). However, such findings based on temperate woody tree species were not directly applicable to herbaceous plants. In this study, 36.9% (GIMMS data) and 55.5% (MODIS data) of the pixels showed negative regression coefficients for chilling days, which indicated that the impact of chilling days is not consistent among pixels. This was in accordance with the results of Cong et al. (2017) which found that the green-up date in the alpine grasslands in the Tibetan Plateau was not directly determined by the reduction in chilling accumulation. Interestingly, we noticed that the green-up date became later at the lower elevation, and became earlier at the higher elevation. Such an opposite trend in spring phenology at different elevations was consistent with a recent study on leaf-out dates of four temperate tree species (Vitasse et al. 2018). The possible reason was that the amount of winter chilling was no longer sufficient at lower elevation due to climatic warming (Vandvik et al. 2018). The insufficient winter chilling at low elevation would lead to an increase in the heat requirements and later spring phenology.

The influence of solar radiation on the spring phenology of grassland was not significant in this study. This result was similar to Miao et al. (2017), which found that the relationship between green-up dates in the Mongolian Plateau grasslands and insolation was less evident. Thus, the effect of radiation on spring phenology in grasslands was weak.

## 5 Conclusion

In this study, we used satellite data to investigate the spatiotemporal pattern of the green-up date of temperate grasslands and its response to four climatic factors in Inner Mongolia, China. The results showed that the green-up dates from different sources (GIMMS and MODIS) exhibited a similar spatial pattern, with the earliest green-up date in the northwest and the latest green-up date in the southwest. In terms of the interannual variations, the green-up dates derived from the MODIS data were consistent with the GIMMS data from 2001 to 2009 but were earlier than the GIMMS data from 2010 to 2015. Over the past 34 years, the green-up dates in grasslands became slightly earlier with a rate of −0.10 day/year (not significant), and this trend was stronger in recent 15 years. Furthermore, our results highlighted that the increased soil moisture presented a consistent promotion effect on the green-up date of grassland for both datasets. However, there were no consistent impacts from accumulated temperature, chilling days, and solar radiation. According to our results, soil moisture was more important than other factors in controlling the interannual changes in the green-up date of temperate grasslands.

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