Characterizing Multiscale Effects of Climatic Factors on the Temporal Variation of Vegetation in Different Climatic Regions of China

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Running title: Multiple temporal scale of climate on vegetation

Characterizing multiscale effects of climatic factors on the temporal variation of vegetation in different climatic regions of China

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Abstract: Vegetation dynamic is sensitive to climatic warming, and is affected by individual or combined climatic factors at different temporal scale with different intensity. Previous studies have unraveled the relationships between vegetation condition and individual climatic factors; however, it is unclear whether the effects of single or combined climatic factors on vegetation dynamic was dominant for different temporal scales, vegetation types, and climatic regions. The objective of this study was to explore the scale-specific univariate and multivariate controls on vegetation over the period 1982–2015 using bivariate wavelet coherency (BWC), multiple wavelet coherence (MWC), and multiple empirical model decomposition (MEMD). The results indicated that the significant vegetation dynamics were mainly located at scales of 1, 0.5, and 0.3 years. The combined explanatory power of the seven climatic factors on the vegetation were greater at the short-term and long-term scales, while the individual climatic factor might affect vegetation dynamic in the seasonal and medium-term scales at some climatic regions. The combined effect of climatic factors in grassland of Tibetan Plateau (TP) and Tempera grassland of Inner Mongolia (TGIM) regions were the greatest, which were 65.06% and 59.53%, respectively. The explanatory powers of climate for crop dynamics between temperate humid & subhumid Northeast China (THSNC) and TP, warm-temperate humid & subhumid North China (WHSNC) and subtropical humid Central & South China (SHCSC), and TGIM and temperate & warm-temperate desert of Northwest China (TWDNC) were equivalent, which were around 47%, 45%, and 39%, respectively. Farming practices in cropland could alleviate the spatial variation of the relationships between climate and vegetation, while enhance the temporal difference of their relationships. Additionally, the dominant influencing factor among different regions varied greatly in the medium-term scale. Collectively, the results might provide alternative perspective for understanding vegetation evolution in response to climatic changes in China.

Keywords: Percentage area of significant coherence (PASC); Bivariate wavelet coherency (BWC); Multivariate wavelet coherence (MWC); NDVI; Scale
1. Introduction

Vegetation, a primary component of terrestrial ecosystem, plays an important role in mitigating soil erosion, regulating terrestrial carbon balance, and providing food for living beings (Ding et al., 2020; Liu et al., 2018; Tong et al., 2016). Moreover, vegetation serves as a sensitive indicator for climatic changes and ecological environment (Sun et al., 2015). Therefore, understanding of vegetation dynamic and its relationships with climatic factors are necessary for reducing the uncertainty in exploring the vegetation feedback to global warming and accurately evaluating terrestrial carbon cycles (Chuai et al., 2020).

Previous studies related to vegetation dynamics and its relationships with long-term series of climatic factors from regional to global spatial scales have been performed, especially with the assistance of satellite-based normalized difference vegetation index (NDVI) (Li et al., 2020), which has been widely used in monitoring vegetation dynamic and exploring the relationships between vegetation and climate changes (He et al., 2012; Zewdie et al., 2017; Zhang et al., 2016). Majority of these studies focused on the original temporal scale, without considering that climatic variables exert an effect on vegetation with different intensity at different temporal scales and different times (Rathinasamy et al., 2019). Thus, quantifying the scale- and temporal-specific climatic driving factors on vegetation variability is necessary for unravelling the vegetation response to climate change.

The scale-dependent variation of climatic factors or the scale-specific relationships between vegetation and individual climatic factor were explored using ensemble empirical mode decomposition (EEMD) (Qi et al., 2019), wavelet transform (WT) (Liu and Menzel, 2016), or the combination of moving windows and linear correlation method (Ning et al., 2019). However, the mechanism of vegetation response to climatic variables is complex and may be concurrently affected by climatic factors. Although the relative importance of mixed climatic factors was quantified using the traditional methods, such as the multivariate regression analysis (Liu et al., 2018) and residual trend method (Sun et al., 2015), the neutralization effect at different scales and times may mislead the interpretation of vegetation variations. Meanwhile, previous studies (Gao et al., 2020; Liu and Menzel, 2016; Zhao and Hu, 2020) reported that the mechanism of vegetation response to climate differed with climatic region and vegetation type. Therefore, the effect of combined climatic factors on vegetation growth should be explored considering the temporal scales,
climatic regions, and vegetation types.

Based on bivariate wavelet coherency (BWC), Hu and Si (2016) proposed a multivariate wavelet coherence (MWC) method, which can be used to detect multivariate relationships in the temporal-scale domain than general multivariate methods because of its ability for identifying localized multivariate relationships. The MWC method has been widely used in a range of areas such as hydrology (Gu et al., 2020), soil science (Centeno et al., 2020), environmental science (Zhao et al., 2018), climate (Song et al., 2020), and economics (Sen and Chaudhury, 2019) for untangling scale-specific and localized multivariate relationships for both spatial and temporal series of data irrespective of stationarity or non-stationarity. Because of its wide applicability we expect that the MWC can be used in ecological science to explore scale-specific and localized effects of multiple climatic factors on vegetation distribution. Therefore, we hypothesize that the response of vegetation to climatic factors differs with temporal scale, climatic condition and vegetation type, which can be identified by the wavelet methods including BWC and MWC.

China has the land area of approximately $960 \times 10^4 \text{ km}^2$ covering approximately 50° of latitude and 62° of longitude, and has extremely diverse climatic conditions (Bai et al., 2020). For clearly unraveling the relations between climate and vegetation across China, different climatic regions were partitioned. The objective of this study was to explore the single or mixed climatic factors on the vegetation growth under different temporal scales, climatic regions, and vegetation types.

Specifically, the univariate relationships between monthly NDVI and single climatic factor were explored using BWC; the multivariate relationships between NDVI and the combined climatic factors were characterized using both MWC and multivariate empirical mode decomposition (MEMD).

2. Material and methods

2.1. Study area

Based on the climatic indexes of active accumulated temperature, aridity index and frost-free period, China can be divided into seven climatic regions (Zhao, 1983), including Temperate humid & subhumid Northeast China (THSNC1), Warm-temperate humid & subhumid North China (WHSNC2), Subtropical humid Central & South China (SHCSC3), Tropic humid South China (THSC), Temperate grassland of Inner Mongolia (TGIM4), Temperate & warm-temperate desert of Northwest China (TWDNC5), and Tibetan Plateau (TP6). In the study, the THSC region was
combined into SHCSC3 region because of the least area of THSC and the similar variations of
vegetation in the both regions. The six climatic regions are shown in Fig. 1a, and the corresponding
climatic indices are shown in Table 1. The aridity index gradually increased from east to west, while
the active accumulated temperature and frost-free period gradually increased from north to south in
the east of China.

2.2 Data sources

A total of 2,474 meteorological stations across China from 1982 to 2015, including the daily
temperature, precipitation, sunshine duration, relative humidity, and wind speed, were collected
from Climatic Data Center, National Meteorological Information Center (https://data.cma.cn/).
After eliminating the meteorological stations with deficient data, the monthly mean temperature
(MT), highest temperature (HT), lowest temperature (LT), accumulated precipitation (AP), sunshine
duration (SSD), relative humidity (RH), or wind speed (WS) were obtained from each station.
The vegetation index of NDVI were derived from the global inventory modeling and mapping
studies (GIMMS) obtained from the national oceanic and atmospheric administration (NOAA)
satellites boarded on the advanced very high resolution radiometer (AVHRR) sensor
(https://ecocast.arc.nasa.gov/data/pub/gimms/). The meteorological stations where the highest
quality of NDVI accounted for more than 85% (quality flags for 1982–2015) were selected, and
their monthly NDVI data from 1982 to 2015 were extracted. Annual land cover map of MODIS
product (MCD12Q1) from 2001 to 2015 across China were obtained from the level-1 and
atmosphere archive and distribution system (LAADS) (https://ladsweb.modaps.eosdis.nasa.gov/).
Only meteorological stations where land use types did not change from 2001 to 2015 were retained
in this study. Because the meteorological stations were mainly located in the grassland or cropland,
only two vegetation types were considered (Fig. 1b).

Based on vegetation type, 564 meteorological stations located in the grassland and cropland were
selected. The spatially-averaged time series of NDVI, MT, HT, LT, AP, SSD, RH, and WS were
calculated over the period 1982–2015, corresponding to two vegetation types in six climatic regions.

2.3 Bivariate wavelet coherency (BWC) and Multiple wavelet coherence (MWC)

The MWC between the response variable Y and predictor variables X (X = [X_1, X_2, ..., X_m]) at
the scale-time (or scale-location) domain (s, τ) is defined as (Hu and Si, 2016):
\[ \rho_{\text{BWC}}^2(s, \tau) = \frac{\overline{W^X_{\text{Y}}(s, \tau)}}{\overline{W^X_{\text{Y}}}(s, \tau) \overline{W^Y_{\text{X}}}(s, \tau)} \]  

When only one variable \((X_i)\) was included in \(X\), Eq. (2) is the equation for BWC, which is expressed as:

\[ \rho_{\text{BWC}}^2(s, \tau) = \frac{\overline{W^Y_{X_i}(s, \tau)}}{\overline{W^Y_{X_i}}(s, \tau) \overline{W^Y_{X_i}}(s, \tau)} \]

where \(\overline{W^Y_{X_i}}(s, \tau)\) is a vector of the smoothed cross-wavelet power spectra, and \(\overline{W^Y_{X_i}}(s, \tau)\) is its complex conjugate. The \(\overline{W^Y_{X_i}}(s, \tau)\) is written as:

\[ \overline{W^Y_{X_i}}(s, \tau) = [\overline{W^Y_{X_i}}(s, \tau) \overline{W^Y_{X_i}}(s, \tau) \ldots \overline{W^Y_{X_i}}(s, \tau)] \]  

The \(\overline{W^X_{X_i}}(s, \tau)\) is a series of the smoothed auto and cross-wavelet power spectra for multivariable \(X\), which is expressed as:

\[ \overline{W^X_{X_i}}(s, \tau) = \begin{bmatrix} \overline{W^X_{X_i}}(s, \tau) & \overline{W^X_{X_i}}(s, \tau) & \ldots & \overline{W^X_{X_i}}(s, \tau) \\ \overline{W^X_{X_i}}(s, \tau) & \overline{W^X_{X_i}}(s, \tau) & \ldots & \overline{W^X_{X_i}}(s, \tau) \\ \vdots & \vdots & \ddots & \vdots \\ \overline{W^X_{X_i}}(s, \tau) & \overline{W^X_{X_i}}(s, \tau) & \ldots & \overline{W^X_{X_i}}(s, \tau) \end{bmatrix} \]

\(\overline{W^Y_{Y}}(s, \tau)\) is the smoothed auto-wavelet power spectra for response variable \(Y\). Both BWC and MWC at 95% significance level are calculated using the Monte Carlo method (Grinsted et al., 2004). A detailed description of BWC can be found in previously studies (Grinsted et al., 2004), and detailed description of MWC can be found in Hu and Si (2016).

2.4 Multivariate empirical mode decomposition (MEMD)

The MEMD is a multivariate extended empirical mode decomposition (EMD) algorithm. To overcome the disadvantage of generating different number of intrinsic mode function (IMF) among multivariate temporal data, MEMD could align common IMFs present within multivariate data. The detailed procedures of MEMD can be found in other publications (Hu et al., 2013; Rehman and Mandic, 2010).

2.5 Data processing

The local wavelet spectra of NDVI for two vegetation types in six climatic regions were calculated to assess the NDVI variations. The BWC between NDVI and each individual climatic factor and MWC between NDVI and the combined climatic factors were calculated, and percentage area of significant coherence (PASC) (Hu et al., 2017; Zhu et al., 2016) was calculated to assess the relative effect of controlling factors on NDVI. Meanwhile, MEMD combined with the squared multiple correlation coefficient was performed for multivariate temporal series. The scales of each
IMF for NDVI and climatic factors were calculated using Hilbert transform, and the mean scales were obtained to represent the characteristic scales. The variance contribution of each IMF to the total variation in NDVI was calculated as the ratio of the variance of each IMF to the variance of the original temporal series of NDVI.

3. Results

3.1 Pearson’s correlation between NDVI and climatic factors

The Pearson’s correlation coefficients between NDVI and climatic factors in six climatic regions and two vegetation types are presented in Table 2. Obviously, temperature and precipitation had consistently positive correlations with vegetation growth. The duration of sunshine and relative humidity also had significant and positive effect on vegetation, while wind speed had significant and negative relationships with NDVI except in the climatic region of TP6. Based on the correlation coefficients, the dominant climatic factors under different regions and vegetation types were similar, and temperature had the greatest correlation with NDVI across China.

3.2 Local wavelet spectra of NDVI

There were distinguishable seasonal patterns across the multiple temporal scales in the local wavelet spectrum of NDVI (Fig. 2). The variation of NDVI around 1-year scale was discerned for the two vegetation types in the six climatic regions. Meanwhile, the seasonality patterns of significant variation around 0.5-year scale were detected for grassland and cropland in the regions of THSNC1, TGIM4, and TP6. The discernable pattern around 0.3-year scale was found in cropland of WHSNC2 and SHCSC3. Additionally, the significant variations around 0.5- and 0.3-year scales entangled with each other after 1995 year in the cropland of SHCSC3. However, in TWDNC5, the seasonal patterns less than 1-year scale were not detected at all.

3.3 Univariate control of climatic factor on NDVI by BWC

The scale- and temporal-specific correlations between NDVI and single climatic factor in grassland are shown in Fig. 3. Because of the similar relationships between NDVI and AT or HT or LT, the BWC between NDVI and HT or LT is not presented. The wavelet coherency between single climatic factor and NDVI were significant around the 1-year scale except the relations between NDVI and SSD in SHCSC3, and the relations between NDVI and SSD or RH or WS in TP6. The effect of precipitation on NDVI around 0.5-year scale was greater than that of temperature for grassland in the regions of THSNC1, WHSNC2, TGIM4, and TP6. Meanwhile, the interannual
effects of precipitation on vegetation were also detected locally or universally in grassland of
WHSNC2, TGIM4, TWDNC5, and TP6.

Overall significant correlations existed in the relationships between NDVI and climatic factor.  
Therefore, the controls of climatic factors on vegetation could be divided into four temporal scales,
including ≤1 years (seasonal), 1–4 years, 4–8 years, and > 8 years. The influential strength of each
individual climatic factors on grass growth is shown in Table 3. For the scales of ≤1 year,
precipitation played a leading role in grassland activity across China except the region of TWDNC5.
For scales of 1–4 years, precipitation controlled the grass growth in the North China of TGIM4 and
TWDNC5, while temperature was the main factor in the rest of China. For scales of 4–8 and > 8
years, the dominant factors varied among TP, MT, AP, RH, and SSD in different climatic regions.
However, the impact of precipitation on grass growth was noticeable at all scales across the entire
China.

The scale- and temporal-specific correlations between NDVI and single climatic factors in
cropland are shown in Fig. 4. The relationships between single climatic factor and NDVI were
captured by the significant wavelet coherency at the temporal scales of 0.5, 1, 4, and 8 years. The
impact of each individual climatic factor on crop growth is shown in Table 4. For scales ≤1 year,
precipitation had a dominantly positive effect on crop growth except the TGIM4 and TWDNC5
regions, while RH in TGIM4, and WS in TWDNC5 played a dominant role in the crop growth. For
the scales of 1–4 years, temperature was the dominant driver for crop growth except precipitation
in THSNC1 region. For the scales of 4–8 and > 8 years, the dominant influencing factors varied
among the climatic factors in different climatic regions.

3.4 Scale- and temporal-specific multivariate control of climatic factors on NDVI by MWC

To compare the effect of individual climatic factors on NDVI, the MWC was used to explore the
combined effect of climatic factors on NDVI. Obviously, the climatic factors explained very well
of the NDVI variations around scales of 1 and 0.5 years (Fig. 5). Although the explanatory capacity
of single climatic factor on grass growth was limited in the region of SHCSC3, the combined
climatic factors could prominently improve the explanatory capacity on vegetation growth at scales
of 1–4 and >8 years.

The PASC values of MWC between NDVI and combined climatic factors for grassland and
cropland are shown in Table 5. Obviously, the mixed effect of climatic factors could slightly increase
the control of single climatic factor on vegetation growth at scales of ≤1 and 1–4 years in most regions, and obviously improved the effect of single climatic factor at scales of >8 years. However, the combined effect was limited in the scales of 4–8 years, with improved effects being observed only in the grassland of TGIM4 and TP6, and the cropland of TWDNC5, where the combined effects at scales of ≤1 year were weaker than that of single climatic driver. It is worth pointing out that the combined effect of climatic factors on vegetation dynamics were greater than that of single climatic factor at the overall temporal scale. In summary, the leading factor for grass variation at scales of ≤1 year was precipitation for TGIM4 and TP6 regions, and was the combination of climate for the other regions; at the scales of 4–8 years, they were RH, precipitation, SSD, combination of climate, precipitation, and the combination for the six climatic regions, respectively; at scales of 1–4 and >8 years, they were the combined climatic factors. For crop growth, the dominant factors at the scales of ≤1 years were RH and WS for TGIM4 and TWDNC5, respectively, and were the climatic combination for the other regions; at scales of 4–8 years, they were HT, WS, precipitation, HT, combined factors, and LT for the six climatic regions, respectively; at the scales of 1–4 and >8 years, the results for cropland were consistent with those for grassland.

The PASC of combined climatic factors ranged from 37% to 65% at the overall temporal scale in grassland, and the effects in different regions ranked in an increase order as SHCSC3 < TWDNC5 < THSNC1 < WHSNC2 < TGIM4 < TP6. The PASC of combined climatic factors ranged from 39% in TGIM4 and TWDNC5 to 45% in WHSNC2 and SHCSC3 and 47% in THSNC1 and TP6 at overall temporal scales in cropland. Therefore, depending on the explanatory power of climatic factors, the agricultural production areas can be classified into four regions of WHSNC2-SHCSC3, TGIM4-TWDNC5, THSNC1, and TP6. The variation of PASC among different climatic regions was obviously lower for cropland than that for grassland, while the variation of PASC among different temporal scales was greater for cropland than that for grassland.

3.5 Comparison of MWC with MEMD

The decomposed components of NDVI by MEMD indicated that MEMD had the advantage to extract information on large trends (see supplementary Fig.S1 and Fig.S2). The averaged scales of NDVI and climatic factors (MT, HT, LT, AP, SSD, RH, and WS) and the variance contribution of each IMF towards original variance of NDVI are presented in Table 6. The shortest scale was 0.99 year represented by IMF1, which contributed the majority variance of above 80%. The result agrees
with that analyzed by wavelet transform which showed that the majority of NDVI variations occurred at scale of around 1 year (Fig. 2).

Coefficients of determination between each scale component of NDVI and climatic factors at the corresponding scale demonstrated that the control of climatic factors on NDVI were the greatest at temporal scales around 1 and > 8 year (see supplementary Fig.S3), which were similar to the results from MWC. However, temperature played a dominant role around 1-year scale across China by MEMD, while precipitation had the leading effect at the scales of ≤1 year at most climatic regions by MWC.

4. Discussion

4.1 Vegetation variation at different temporal scales

The impact of land cover change on vegetation growth is complicated because it does not only depend on the intensity but also on the type of land-cover change (Gao et al., 2020). In the study, the land types during 1982–2000 were not considered because the major shift in land use types have taken place after 2000, such as urbanization caused the conversion from croplands to construction land, the Grain for Green Projection caused the conversion from cropland to forest. Thus, to precisely evaluate the vegetation–climate variation at multiple temporal scales, the land types maintained from 2001 to 2015 were extracted in the study to minimize the heterogeneity of anthropogenic factors on vegetation.

The local variation of grass and crop NDVI were significant around the 1-year scale across the entire China over the period of 1982–2015. The variation of vegetation around 1-year scale was also observed by Liu et al. (2016). In the study, the significant variations of NDVI around 0.3- and 0.5-year scale were also detected at the confidence level of 68%. Thus, the temporal scale of the significant variation of NDVI was 1 year followed by 0.5 and 0.3 year depending on the climatic regions and vegetation types. The significant variation of NDVI at 0.5-year scale could be perceived across China except the grassland of SHCSC3, the cropland of WHSNC2, and the grassland and cropland of TWDNC5. Because of the intensity of economy-driven anthropologic factors, the frequent human activity in the southeast of China (Hou et al., 2015) might lead to the indiscernibility of patterns around <1 year scale in the grassland of SHCSC3. In the cropland of WHSNC2, the variation around 0.5-year scale was insignificant, while the variation around 0.3-year scale was significant. The result might be related to the cropping system of winter wheat and spring maize (or
summer maize) uniformly applied in this area (Yan et al., 2020). In the TWDNC5 region, because of the lowest NDVI value across the whole year and the driest climatic conditions (Zhao and Hu, 2020), the vegetation growth did not display the seasonal variations at scales of <1 years. Notably, the seasonal pattern around 0.5-year scale was prominent in the THSNC1, TGIM4, and TP6 regions, which might be attributed to the difference between vegetation season and non-vegetation season (Zhou et al., 2020). The mingled seasonal patterns at 0.5- and 0.3-year scales in the cropland of SHCSC3 might be attributed to the mixed cropping system of double-rice cropping and rice-wheat cropping after 1995 year (Wu et al., 2013; Zhang et al., 2015). Therefore, the vegetation variation was dominant by the 1-year scale across the entire China, the variation at 0.5-year scale was found in the temperate area and Tibetan Plateau with distinct difference between vegetation season and non-vegetation season during one year, and the significant variation at 0.3-year scale was found generally under the cropland in the major crop producing area of the Southeast China (WHSNC2 and SHCSC3) with multiple cropping system.

4.2 Effect of single climatic factor on NDVI at multiple temporal scales

Previously studies reported that precipitation, temperature, solar radiation, and relative humidity were significantly correlated with vegetation growth in China (Sun et al., 2020; Yang and Zhang, 2014; Zhao and Hu, 2020). The climatic factors, including MT, HT, LT, AP, SSD, RH, and WS, were selected in the present study. We observed that the correlation between temperature and vegetation was positive at scales >0.5 years and was negative at scales ≤0.5 years. Temperature exerted either dominantly positive effect or negative effect on vegetation growth at some scales was in agreement with previous observation in Southwest China (Liu and Menzel, 2016). The noticeable positive relationships between temperature and vegetation at scales larger than 0.5-year might be attributed to more carbohydrate consumption and subsequently enhancement of daytime photosynthesis persistently, which resulted from the nighttime warming optimizing both root and leaf respiration of plants (Yuan et al., 2020). The negative effects of temperature on vegetation at less than 0.5-year scale were probably associated with the short-time limited water availability (Jiang et al., 2020), resulted from the increasing evaporation because of the increase in the highest temperature, constrained photosynthetic activities and aggravated plant respiration, and thus inhibited plant growth. Therefore, temperature exerted different effects on vegetation growth at different temporal scales.
Precipitation had pronounced positive effect on vegetation growth around 1-year scale, which
was different from the results from Southwest Germany (Liu and Menzel, 2016), which might be
attributed to the different climatic conditions between Germany and China. However, the positive
correlation between precipitation and NDVI was observed in the Yangtze River and Yellow River
Basin at some temporal scales (Zhang et al., 2020). Although precipitation was not the greatest
influencing factor for grass growth based on the Pearson’s correlation coefficient, it played a leading
role across the entire China at overall temporal scales and seasonal scale except the TWDNC5
region. Precipitation was not the leading factor for grass growth at the seasonal scale (≤ 1 years) in
TWDNC5, but it had a critical effect at the scales of 1–4 and 4–8 years, and overall temporal scales.
In TGIM4 region, precipitation had a critical effect on grass growth at any temporal scales, which
was consistent with previous finding that water availability dominated grass productivity in the
region (Zhao and Hu, 2020). For cropland at the seasonal scale (≤ 1 years), precipitation also played
a leading role in the major crop producing areas (THSNC1, WHSNC2, and SHCSC3) and TP6, and
RH had the dominant effect on crop productivity in TGIM4. In TWDNC5 region, precipitation
seemed to exert the dominant influence on crop growth only at the scales of 4–8 years, probably
because irrigation activities in the area disorganized the crop-precipitation relations, and the inter-
annual variation of precipitation is greater than its intra-annual variation (Linscheid et al., 2020),
which resulted in the leading effect at the scales of 4–8 years.

It is worth pointing out that SSD, which relates to solar radiation, was positively related with
growth growth across the 1-year scale except the regions of SHCSC3 and TP6, while it had unstable
effect on vegetation dynamic at other temporal scales. The local negative effect of SSD on
vegetation might be related to the increased evaporation, and thus the increase of SSD caused water
losses, further preventing plant from growth. In SHCSC3, SSD did not have stable relationships
with grass condition around 1-year scale, which might be because of the discrepancy between SSD
and the critical factor of temperature. The higher temperature resulted from closing to the equator,
and the lower SSD. In TP6, SSD was slightly correlated with grass at 1-year scale, which agrees
with a previous finding (Zhao and Hu, 2020) that SSD explained less in alpine grasslands than that
in temperate grasslands. The result might be attributed to the complex topology in TP6, which
resulted in the large variations in SSD.

Compared with precipitation, RH had relatively weak effects on the vegetation growth especially
The complex topology in TP6, which makes the spatial distribution of climatic conditions much more heterogeneous, resulted in the varied mechanism of vegetation-climate dynamics. Meanwhile, the response of alpine grass to climate, which was distributed in TP6, was different from the temperate grassland. The slightly weak effect of relative humidity on crop productivity in THSNC1 might be attributed to the irrigation activities for crop in the area.

The WS exerted negative influence on vegetation productivity at 1- and 0.5-year scales, especially in temperate regions and Tibetan Plateau with the distribution of strong wind. The noticeable impacts of WS on the vegetation growth were probable due to mechanical destruction and excessive transpiration of plant resulted from strong wind (Gardiner et al., 2016), which is extremely injurious to a plant. However, the positive relationships between WS and vegetation were also observed in some localized time, because wind can increase turbulence in the atmosphere and availability of CO\textsubscript{2} and thereby increased photosynthesis (Konrad et al., 2021). Unfortunately, the effect of WS on vegetation dynamic was not captured by Pearson’s correlation coefficient in TP6 region.

We concluded that precipitation played a crucial role in affecting the seasonal variation of vegetation productivity resulted from the prominent effect around 0.5-year scale, temperature played a leading role in affecting the variation of vegetation at the scales of 1–4 years. Thus, the leading single-factor is annual oscillation of temperature, combined with 0.5–year intraannual dominance of precipitation. For scales of 4–8 and >8 years, the dominant factor on vegetation varied with climatic regions and vegetation types, which implied that the mechanisms by which vegetation respond to single climatic factor were various among different regions and vegetation types at these temporal scales.

4.3 Combined effect of climatic factors on NDVI at multiple temporal scales

Our results showed that the interaction effects of multiple climatic factors on vegetation dynamic were stronger than the effect of individual climatic variables on NDVI at scales of >8 years. Such long-term climate variation may occur in the form of periodic atmospheric fluctuations (Linscheid et al., 2020), which might result in the long-term variation of NDVI. The combined climatic controls on NDVI were evaluated by previous studies. For example, Qu et al. (2020) distinguished the impacts of climate change and anthropogenic factors on vegetation dynamics based on partial derivation in the Yangtze River Basin, which were 70% and 30%, respectively. However, it is
unclear whether the effects of single or the combined climatic factors on vegetation dynamic was
dominant for different temporal scales, vegetation types, and climatic regions. For scales of ≤1 year
and 4–8 years, single climatic factor played a dominant role in controlling the dynamic of vegetation
in some climatic regions. The results confirmed that precipitation has a critical effect on grass
productivity in Inner Mongolia and Tibetan Plateau (Zhao and Hu, 2020), and wind has a critical
effect on crop productivity in Xinjiang at the seasonal scale. However, at the scales of 4–8 years,
the climatic variables exerted different influences depending on the climatic regions and vegetation
types, which might be attributed to the large variations at these temporal scales. For example, the
climatic events of short-term concurrent hot and dry extreme (SCHDE) over the Pearl river basin
was detected with larger variations at the temporal scale 4–8 years, which was negatively correlated
with Niño3.4 index around scales of 4 year (Zhang et al., 2019). Meanwhile, variations in daily
minimum temperature greater than 90th percentile or daily maximum temperature greater than 90th
percentile were also dominant at temporal scales 4–8 years over the period 1960–2015 in Yangtze
River Basin (Cui et al., 2019). At the scales of 1–4 and >8 years, the combination of climate exerted
more important influence on vegetation growth across the entire China.

In our study, the explanatory capability of the climatic combination on grass growth ranked as
SHCSC3 < TWDNC5 < THSNC1 (or WHSNC2) < TGIM4 < TP6; it ranked as TGIM4 (or
TWDNC5) < WHSNC2 (or SHCSC3) < THSNC1 (or TP6) in terms of the effects on crop growth.
The result indicated that socioeconomic condition is related to the dynamics of grass growth except
TWDNC5 with the lowest NDVI values (Yao et al., 2019). The less variation of explanatory power
among different regions demonstrated that tillage activities in cropland alleviated the spatial
difference of climate-vegetation dynamics, and strengthened their temporal difference. Meanwhile,
the greatest variation at scales of 4–8 years implied that the climatic regions and vegetation types
cannot be neglected in the analysis of vegetation growth at these temporal scales.

4.4 Comparison of MWC and MEMD on the multivariate relationships in ecology

The vegetation-climate relationships at scales around 1 year and > 8 year were dominant, which
were similar for both MWC and MEMD. The result demonstrated that both MWC and MEMD
could unravel the dominant temporal scales of NDVI variation. However, the discrepancy of
dominant factors at the seasonal scales among MEMD and MWC might be attributed to the shortage
of vegetation–climate relations at 0.5-year scales for MEMD, where precipitation had a dominant
effect on vegetation. MEMD can partition original series into limited temporal scales, and generally attributed dominant variance to the seasonal process in ecology, which was consistent with previous study finding that IMFs decomposed by EMD contained more variation in the seasonal cycle and less modulation in the interannual temporal scales for NDVI (Linscheid et al., 2020). In addition, other methods, such as multiple regression or local correlation methods, should be integrated into MEMD for yielding the combined scale-specific effect of climate on vegetation, or obtaining their localized multivariate relationships. Our result indicated that the residue decomposed by MEMD could represent the trend of vegetation growth.

Although both WMC and MEMD could capture the significant relations of vegetation-climate at the temporal scales around 1 and >8 years, the distinction between both methods should be mastered and the appropriate one can be applied depending on the situation. The study paves a way for better understanding the scale-specific, localized temporal heterogeneity of vegetation growth response to climate variability, and the temporal evolution of vegetation dynamics at different climatic regions should be explored in the future.

5. Conclusion

The following conclusions were made:

(1) The vegetation variation at 1-year scale could be captured across the entire China, vegetation variation at 0.5-year scale was displayed in the temperate area and Tibetan Plateau with distinct difference between vegetation season and non-vegetation season during one year, and the significant variation at 0.3-year scale happened generally in the major crop producing area of the Southeast China (WHSNC2 and SHCSC3) with multiple cropping system.

(2) For individual climatic factor, precipitation had a dominant effect on vegetation at the seasonal scale (<1 years) because of their significant relations around 0.5-year scale, temperature had a dominant effect on vegetation at the scales of 1–4 years, and the leading factor on vegetation varied with climatic regions at the scales of 4–8 and >8 years.

(3) The combination of climatic factors could promote the control on vegetation growth at the scales of 1–4 and >8 years across the entire China. Climatic regions and vegetation types cannot be neglected in the analysis of vegetation growth at the temporal scales of 4–8 year.

(4) The greatest mixed effect of climatic factors on grass growth was around 65% in Tibetan Plateau, and the greatest effect on crop growth was around 47% in the Tibetan Plateau and Northeast
China. The effect of tillage activities on crop growth could alleviate the spatial variation of the vegetation-climate relations, while enhance the temporal difference of their relationships.

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**Availability of data mand material** The climate data are available from Climatic Data Center, National Meteorological Information Center (https://data.cma.cn/). The NDVI were derived from the global inventory modeling and mapping studies (GIMMS) obtained from the national oceanic and atmospheric administration (NOAA) satellites boarded on the advanced very high resolution radiometer (AVHRR) sensor (https://ecocast.arc.nasa.gov/data/pub/gimms/). Annual land cover map of MODIS product (MCD12Q1) from 2001 to 2015 across China were obtained from the level-1 and atmosphere archive and distribution system (LAADS) (https://ladsweb.modaps.eosdis.nasa.gov/).

**Code availability** software: MATLAB, R.

**Declarations**

**Ethics approval** Not applicable.

**Consent to participate** Not applicable.

**Consent to publication** Not applicable.

**Conflict of interest** The authors declare no conflict of interest.
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in the Fen River basin on the Chinese Loess Plateau. *Catena* 147: 764–772.
| Climatic regions | Area percentage (%) | Active accumulated temperature (℃) | Aridity index (-) | Frost-free period (d) |
|------------------|---------------------|-------------------------------------|------------------|----------------------|
| Temperate humid & subhumid Northeast China (THSNC1) | 9.35 | 1400–3200 | 0.5–1.2 | < 145 |
| Warm-temperate humid & subhumid North China (WHSNC2) | 11.50 | 3200–4500 | 0.5–1.5 | 150–200 |
| Subtropical humid Central & South China (SHCSC3) | 24.94 | > 4500 | 0.5–1.0 | whole year |
| Temperate grassland of Inner Mongolia (TGIM4) | 6.41 | 2000–3000 | 1.2–4.0 | < 180 |
| Temperate & warm-temperate desert of Northwest China (TWDNC5) | 17.90 | 3200–4500 | > 4.0 | Around 200 |
| Tibetan Plateau (TP6) | 29.89 | < 3000 | 0.5–4.0 | < 130 |
| Vegetation type | Climatic region | MT   | HT   | LT   | AP   | SSD  | RH   | WS   |
|----------------|----------------|------|------|------|------|------|------|------|
| Grassland      | THSNC1         | 0.88* | 0.87**| 0.89**| 0.78**| 0.41**| 0.66**| -0.37**|
|                 | WHSNC2         | 0.88**| 0.87**| 0.90**| 0.85**| 0.39**| 0.58**| -0.30**|
|                 | SHCSC3         | 0.63**| 0.64**| 0.63**| 0.57**| 0.15**| 0.39**| -0.14**|
|                 | TGIM4          | 0.89**| 0.88**| 0.90**| 0.85**| 0.60**| 0.15**| -0.34**|
|                 | TWDNC5         | 0.93**| 0.93**| 0.93**| 0.69**| 0.79**| 0.76**| -0.57**|
|                 | TP6            | 0.88**| 0.88**| 0.88**| 0.93**| 0.31**| 0.22**| -0.08**|
| Cropland        | THSNC1         | 0.90**| 0.90**| 0.91**| 0.82**| 0.49**| 0.15**| -0.26**|
|                 | WHSNC2         | 0.90**| 0.89**| 0.91**| 0.78**| 0.45**| 0.36**| -0.11**|
|                 | SHCSC3         | 0.90**| 0.89**| 0.90**| 0.74**| 0.36**| 0.15**| -0.38**|
|                 | TGIM4          | 0.88**| 0.87**| 0.90**| 0.75**| 0.63**| 0.71**| -0.58**|
|                 | TWDNC5         | 0.89**| 0.89**| 0.90**| 0.58**| 0.84**| 0.57**| -0.42**|
|                 | TP6            | 0.90**| 0.90**| 0.91**| 0.88**| 0.68**| 0.35**| -0.07**|

* Significant at $P < 0.05$; ** Significant at $P < 0.01$. THSNC1: Temperate humid & subhumid Northeast China; WHSNC2: Warm-temperate humid & subhumid North China; SHCSC3: Subtropical humid Central & South China; TGIM4: Temperate grassland of Inner Mongolia; TWDNC5: Temperate & warm-temperate desert of Northwest China; and TP6: Tibetan Plateau.
Table 3 Percentage area of significant coherence (PASC, %) of BWC between NDVI and single climatic factor at different scales for grassland under six climatic regions.

| Climatic region | Climatic factor | ≤ 1 years | 1–4 years | 4–8 years | > 8 years | Overall temporal scales | Type of Correlation around 1 year |
|-----------------|----------------|-----------|-----------|-----------|-----------|------------------------|---------------------------------|
| THSNC1          | AP             | 49.58     | 29.62     | 0.00      | 17.61     | 30.48                  | Positive                        |
|                 | SSD            | 33.95     | 27.60     | 0.00      | 24.62     | 17.61                  | Positive                        |
|                 | RH             | 48.40     | 29.24     | 0.00      | 30.15     | 27.97                  | Positive                        |
|                 | WS             | 42.17     | 36.41     | 0.69      | 29.60     | 27.97                  | Negative                        |
| WHSNC2          | AP             | 45.71     | 40.48     | 28.17     | 0.00      | 36.70                  | Positive                        |
|                 | SSD            | 25.88     | 27.67     | 0.00      | 19.99     | 17.61                  | Positive                        |
|                 | RH             | 34.33     | 27.31     | 0.00      | 23.08     | 24.62                  | Positive                        |
|                 | WS             | 36.65     | 31.21     | 0.00      | 25.43     | 24.62                  | Negative                        |
| SHCSC3          | AP             | 29.95     | 30.17     | 22.97     | 0.00      | 22.42                  | Positive                        |
|                 | SSD            | 10.63     | 23.37     | 0.00      | 12.86     | 17.61                  | Positive                        |
|                 | RH             | 22.86     | 25.38     | 0.00      | 17.82     | 19.99                  | Positive                        |
|                 | WS             | 20.02     | 26.96     | 0.00      | 17.18     | 17.61                  | Negative                        |
| TGIM4           | AP             | 51.71     | 53.03     | 49.65     | 44.33     | 51.15                  | Positive                        |
|                 | SSD            | 29.94     | 31.59     | 23.79     | 0.00      | 23.41                  | Positive                        |
|                 | RH             | 38.50     | 25.68     | 5.60      | 25.25     | 23.79                  | Positive                        |
|                 | WS             | 38.03     | 34.94     | 16.50     | 29.92     | 23.79                  | Negative                        |
| TWDNC5          | AP             | 30.61     | 50.95     | 33.15     | 3.82      | 35.62                  | Positive                        |
|                 | SSD            | 28.53     | 45.27     | 12.50     | 0.00      | 28.75                  | Positive                        |
|                 | RH             | 26.86     | 36.60     | 15.67     | 6.97      | 25.41                  | Positive                        |
|                 | WS             | 32.90     | 32.38     | 5.25      | 25.09     | 23.79                  | Negative                        |

The dominantly influencing factors at different scales are shown in bold. THSNC1: Temperate humid & subhumid Northeast China; WHSNC2: Warm-temperate humid & subhumid North China; SHCSC3: Subtropical humid Central & South China; TGIM4: Temperate grassland of Inner Mongolia; TWDNC5: Temperate & warm-temperate desert of Northwest China; and TP6: Tibetan Plateau.
### Table 4
Percentage area of significant coherence (PASC, %) of BWC between NDVI and single climatic factor at different scales for cropland under six climatic regions.

| Climatic region | Climatic factor | ≤ 1 years | 1–4 years | 4–8 years | > 8 years | Overall | Temporal scale | Type of correlation around 1 year |
|-----------------|----------------|-----------|-----------|-----------|-----------|---------|---------------|----------------------------------|
|                 |                | ≤ 1 years | 1–4 years | 4–8 years | > 8 years |         |               |                                  |
| THSNC1          | MT             | 37.97     | 39.41     | 12.42     | 10.57     | 31.67   | Positive     |                                  |
|                 | HT             | 38.64     | 38.44     | 16.05     | 10.08     | 32.64   | Positive     |                                  |
|                 | LT             | 33.67     | 40.65     | 10.01     | 15.09     | 30.19   | Positive     |                                  |
|                 | AP             | 49.93     | 45.05     | 11.19     | 57.25     | 42.65   | Positive     |                                  |
|                 | SSD            | 32.36     | 33.09     | 1.49      | 45.13     | 30.90   | Positive     |                                  |
|                 | RH             | 25.10     | 9.95      | 0.00      | 0.00      | 13.55   | Positive     |                                  |
|                 | WS             | 40.65     | 31.94     | 0.00      | 0.00      | 27.46   | Negative     |                                  |
| WHSNC2          | MT             | 29.74     | 42.70     | 0.00      | 22.65     | 28.92   | Positive     |                                  |
|                 | HT             | 29.57     | 41.61     | 0.00      | 0.35      | 26.46   | Positive     |                                  |
|                 | LT             | 32.78     | 40.07     | 6.27      | 40.16     | 31.76   | Positive     |                                  |
|                 | AP             | 44.83     | 32.59     | 12.83     | 0.00      | 31.43   | Positive     |                                  |
|                 | SSD            | 22.77     | 19.82     | 0.00      | 0.00      | 15.97   | Positive     |                                  |
|                 | RH             | 22.87     | 20.65     | 4.11      | 0.00      | 17.13   | Positive     |                                  |
|                 | WS             | 21.87     | 21.86     | 20.83     | 20.83     | 23.72   | Negative     |                                  |
| SHCSC3          | MT             | 30.98     | 37.44     | 6.31      | 16.81     | 27.58   | Positive     |                                  |
|                 | HT             | 34.45     | 40.44     | 4.29      | 0.00      | 28.29   | Positive     |                                  |
|                 | LT             | 28.49     | 34.26     | 3.49      | 19.96     | 26.25   | Positive     |                                  |
|                 | AP             | 43.58     | 31.88     | 22.20     | 2.24      | 31.63   | Positive     |                                  |
|                 | SSD            | 29.39     | 19.04     | 18.73     | 62.50     | 27.99   | Positive     |                                  |
|                 | RH             | 27.54     | 26.62     | 5.35      | 0.00      | 21.07   | Positive     |                                  |
|                 | WS             | 25.29     | 30.46     | 8.95      | 53.19     | 27.40   | Negative     |                                  |
| TGIM4           | MT             | 30.99     | 36.88     | 10.64     | 0.00      | 26.95   | Positive     |                                  |
|                 | HT             | 34.25     | 37.25     | 14.11     | 2.21      | 28.83   | Positive     |                                  |
|                 | LT             | 27.57     | 36.18     | 5.37      | 0.00      | 24.18   | Positive     |                                  |
|                 | AP             | 43.41     | 30.85     | 0.00      | 0.00      | 28.16   | Positive     |                                  |
|                 | SSD            | 26.41     | 36.28     | 8.54      | 0.00      | 24.02   | Positive     |                                  |
|                 | RH             | 46.66     | 29.49     | 0.00      | 0.00      | 29.02   | Positive     |                                  |
|                 | WS             | 40.31     | 27.08     | 1.14      | 0.00      | 26.07   | Negative     |                                  |
| TWDNC5          | MT             | 38.22     | 40.34     | 0.00      | 0.00      | 29.31   | Positive     |                                  |
|                 | HT             | 36.44     | 39.97     | 0.00      | 0.00      | 28.21   | Positive     |                                  |
|                 | LT             | 41.71     | 41.10     | 0.00      | 0.00      | 30.68   | Positive     |                                  |
|                 | AP             | 29.88     | 33.66     | 1.59      | 0.00      | 23.68   | Positive     |                                  |
|                 | SSD            | 24.79     | 30.89     | 0.00      | 0.00      | 20.01   | Positive     |                                  |
|                 | RH             | 29.69     | 30.64     | 0.00      | 0.00      | 22.31   | Positive     |                                  |
|                 | WS             | 44.05     | 35.96     | 0.00      | 0.00      | 30.26   | Negative     |                                  |
| TP6             | MT             | 35.57     | 40.76     | 14.97     | 7.70      | 32.56   | Positive     |                                  |
|                 | HT             | 36.08     | 39.27     | 11.11     | 0.00      | 29.76   | Positive     |                                  |
|                 | LT             | 36.74     | 40.64     | 21.53     | 50.00     | 36.69   | Positive     |                                  |
|                 | AP             | 45.43     | 36.11     | 3.13      | 0.00      | 31.20   | Positive     |                                  |
|                 | SSD            | 27.62     | 30.00     | 0.00      | 0.00      | 21.61   | Positive     |                                  |
|                 | RH             | 35.86     | 26.99     | 4.60      | 0.00      | 24.60   | Positive     |                                  |
|                 | WS             | 38.46     | 32.40     | 2.31      | 19.89     | 28.84   | Negative     |                                  |

The dominantly influencing factors at different scales are shown in bold. THSNC1: Temperate humid & subhumid Northeast China; WHSNC2: Warm-temperate humid & subhumid North China; SHCSC3: Subtropical humid Central & South China; TGIM4: Temperate grassland of Inner Mongolia; TWDNC5: Temperate & warm-temperate desert of Northwest China; and TP6: Tibetan Plateau.
Table 5  Percentage area of significant coherence (PASC, %) of MWC between NDVI and combined climatic factors at different scales under different climatic regions.

| Vegetation type | Climatic region | ≤ 1 years | 1–4 years | 4–8 years | > 8 years | Overall Temporal scale | CV \(^d\) |
|-----------------|-----------------|-----------|-----------|-----------|-----------|------------------------|---------|
| Grassland       | THSNC1          | 53.70 (49.58) \(^a\) | 43.00 (40.79) \(^a\) | 3.41 (4.49) \(^b\) | 90.48 (17.61) \(^a\) | 45.56 (30.48) \(^a\) | 75.18   |
|                 | WHSNC2          | 48.92 (45.71) \(^a\) | 49.84 (41.00) \(^a\) | 21.12 (28.17) \(^b\) | 61.34 (22.97) \(^a\) | 45.88 (36.70) \(^a\) | 37.71   |
|                 | SHCSC3          | 33.93 (29.95) \(^a\) | 51.70 (35.56) \(^a\) | 0.33 (5.74) \(^b\) | 70.10 (0.00) \(^a\) | 37.66 (22.42) \(^a\) | 76.17   |
|                 | TGIM4           | 50.26 (51.71) \(^b\) | 58.35 (53.03) \(^a\) | 66.22 (49.65) \(^a\) | 93.17 (44.33) \(^a\) | 59.53 (51.15) \(^a\) | 27.80   |
|                 | TWDNC5          | 41.01 (38.09) \(^a\) | 52.03 (50.95) \(^a\) | 4.47 (33.15) \(^b\) | 66.81 (6.97) \(^a\) | 41.10 (35.62) \(^a\) | 64.74   |
|                 | TP6             | 53.81 (57.61) \(^b\) | 69.41 (43.55) \(^a\) | 67.61 (32.11) \(^a\) | 95.59 (68.31) \(^a\) | 65.06 (46.20) \(^a\) | 24.36   |
|                 | CV \(^c\)       | 16.84     | 16.63     | 116.26    | 19.02     | 21.95                  | -       |
| Cropland        | THSNC1          | 54.13 (49.93) \(^a\) | 45.80 (45.05) \(^a\) | 1.47 (16.05) \(^b\) | 99.75 (65.13) \(^a\) | 47.20 (42.65) \(^a\) | 80.08   |
|                 | WHSNC2          | 49.70 (44.83) \(^a\) | 50.14 (42.70) \(^a\) | 10.83 (20.83) \(^b\) | 73.35 (50.42) \(^a\) | 45.78 (31.76) \(^a\) | 56.35   |
|                 | SHCSC3          | 50.22 (43.58) \(^a\) | 41.77 (40.44) \(^a\) | 11.56 (22.20) \(^b\) | 99.75 (62.50) \(^a\) | 45.90 (31.63) \(^a\) | 72.00   |
|                 | TGIM4           | 41.19 (46.66) \(^b\) | 41.52 (37.25) \(^a\) | 1.06 (14.11) \(^b\) | 92.19 (2.21) \(^a\) | 39.62 (28.83) \(^a\) | 84.86   |
|                 | TWDNC5          | 41.55 (44.05) \(^b\) | 43.76 (41.10) \(^a\) | 6.31 (1.59) \(^a\)  | 74.30 (0.00) \(^a\) | 39.65 (30.68) \(^a\) | 67.03   |
|                 | TP6             | 50.94 (45.43) \(^a\) | 50.42 (40.76) \(^a\) | 16.95 (21.53) \(^b\) | 73.46 (50.00) \(^a\) | 47.39 (36.69) \(^a\) | 49.38   |
|                 | CV \(^c\)       | 11.11     | 8.70      | 77.66     | 15.01     | 8.22                   | -       |

Number in bracket is the PASC of the leading single factor with NDVI.

\(^a\) The combined effect of climatic factors is greater than the leading single-factor.

\(^b\) The combined effect of climatic factors is less than the leading single-factor.

\(^c\) Coefficient of variance for PASC among different regions.

\(^d\) Coefficient of variance for PASC among different temporal scales.

THSNC1: Temperate humid & subhumid Northeast China; WHSNC2: Warm-temperate humid & subhumid North China; SHCSC3: Subtropical humid Central & South China; TGIM4: Temperate grassland of Inner Mongolia; TWDNC5: Temperate & warm-temperate desert of Northwest China; and TP6: Tibetan Plateau.
Table 6 Characteristic scale (year) of each intrinsic mode function (IMF) of NDVI and the percent of variance (year) explained by each IMF and residue under different vegetation type and climatic regions.

| Vegetation type | Climatic region  | IMF1 | IMF2 | IMF3 | IMF4 | IMF5 | IMF6 | Residue |
|-----------------|------------------|------|------|------|------|------|------|---------|
| Grassland       | THSNC1           | 0.99 | 3.00 | 6.92 | 8.16 | 24.56| –     | –       |
|                 | WHSNC2           | 0.99 | 2.27 | 3.99 | 5.32 | 9.29 | –     | –       |
|                 | SHCSC3           | 0.97 | 2.15 | 3.94 | 7.77 | 11.61| 12.73|         |
|                 | TGIM4            | 0.99 | 2.81 | 4.98 | 9.68 | –    | –     | –       |
|                 | TWDNC5           | 0.99 | 3.24 | 5.35 | 9.31 | –    | –     | –       |
|                 | TP6              | 1.00 | 2.99 | 5.25 | 7.81 | 10.78| –     | –       |
| Cropland        | THSNC1           | 1.00 | 3.01 | 4.92 | 7.85 | 17.78| –     | –       |
|                 | WHSNC2           | 0.99 | 2.09 | 3.76 | 6.26 | 8.25 | 15.81| –       |
|                 | SHCSC3           | 0.99 | 2.42 | 4.19 | 6.28 | 14.27| 15.39|         |
|                 | TGIM4            | 0.99 | 2.91 | 5.70 | 6.44 | –    | –     | –       |
|                 | TWDNC5           | 0.99 | 2.99 | 7.62 | 10.13| –    | –     | –       |
|                 | TP6              | 0.99 | 2.47 | 4.67 | 7.41 | 11.61| –     | –       |

THSNC1: Temperate humid & subhumid Northeast China; WHSNC2: Warm-temperate humid & subhumid North China; SHCSC3: Subtropical humid Central & South China; TGIM4: Temperate grassland of Inner Mongolia; TWDNC5: Temperate & warm-temperate desert of Northwest China; and TP6: Tibetan Plateau.
Figure caption

**Fig. 1.** (a) Geographic distribution of selected meteorological stations and natural climatic regions, and (b) Vegetation types in China.

**Fig. 2.** Local wavelet spectrum of mean NDVI under two land types (grassland and cropland) in the six climatic regions. X-axis represents the real time from 1981 to 2015; Y-axis represents temporal scale in year. The solid black lines designate the variance of NDVI at a confidence level of 68%, and color bar represents strength of variance.

**Fig. 3.** BWC between NDVI and single climatic factor under grassland in the six climatic regions. X-axis represents the real time from 1981 to 2015, and Y-axis represents temporal scale in year. The solid black lines represent 95% confidence level, color bar represents strength of correlation, and direction of arrow represents the type of correlation (right pointing arrows being positive and left pointing arrows being negative).

**Fig. 4.** BWC between NDVI and single climatic factor under cropland in the six climatic regions.

**Fig. 5.** MWC between NDVI and seven-factor combination of MT, HT, LT, AP, SSD, RH, WS under two vegetation types in the six climatic regions. Solid black lines represent significant coherence at 95% confidence level. Solid white lines indicate NDVI variation at 68% confidence level.
Fig. 1.
Fig. 2.
Fig. 3.
Fig. 5.
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