Spatial and Temporal Variability of Key Bio-Temperature Indicators and their Effects on Vegetation Dynamics in the Great Lakes Region of Central Asia

Xuan Gao
Institute of Geographic Sciences and Natural Resources Research
Dongsheng Zhao (zhaods@igsnrr.ac.cn)
Institute of Geographic Sciences and Natural Resources Research
Lei Liu
Institute of Geographic Sciences and Natural Resources Research

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Abstract

Dryland ecosystems are fragile to climate change due to harsh environmental condition. Climate change affects vegetation growth primarily by altering some key bio-temperature thresholds. Key bio-temperatures are closely related to vegetation growth, and slight changes could produce substantial effects on ecosystem structure and function. Therefore, this study selected the number of days with daily mean temperature above 0 °C (DT_0), 5 °C (DT_5), 10 °C (DT_{10}), 20 °C (DT_{20}), the start of growing season (SGS), the end of growing season (EGS), and the length of growing season (LGS) as bio-temperature indicators to analyze the response of vegetation dynamics to climate change in the Great Lakes Region of Central Asia (GLRCA) for the period 1982–2014. On the regional scale, DT_0, DT_5, DT_{10}, and DT_{20} exhibited an overall increasing trend. Spatially, most of the study area showed that the negative correlation between DT_0, DT_5, DT_{10}, DT_{20} with annual NDVI increased with increasing bio-temperature thresholds. Especially, more than 88.3% of the study area showed a negative correlation between annual NDVI and DT_{20}, as increased DT_{20} exacerbated ecosystem drought. Moreover, SGS exhibited insignificantly advanced trend, and EGS experienced a significantly delayed trend. The overall extending trend in LGS was mainly attributed to the delayed EGS. Besides, our study revealed that about 54.7% of the study area showed a negative correlation between annual NDVI and LGS, especially in the north, indicating a negative effect of climate warming on vegetation growth in the drylands. The results of this study will help assess the stability of vegetation to climate variability, and predict the response of vegetation to future climate change in the GLRCA.

1. Introduction

Global surface temperature was 1.09°C higher in 2011–2020 than 1850–1900, with larger increases over land (1.59°C) than over the ocean (0.88°C) (IPCC 2021). Climate change characterized by global warming has a greater impact on the structure and function of terrestrial ecosystems (Cheng et al. 2021; Holst et al. 2013). Climate warming has intensified glacier melting and permafrost degradation (Bolch et al. 2010; Zheng et al. 2020), resulting in a series of ecological and environmental effects, such as the release of large amounts of deep permafrost carbon and declining water table (Wang et al. 2020). Meanwhile, climate warming enhanced vegetation productivity by promoting photosynthesis, extending growing seasons, especially at high latitudes and altitudes (Piao et al. 2007; Wang et al. 2011; Wei et al. 2018). In addition, plenty of evidence suggests that extreme high temperature events are increased with enhancement of frequency and intensity across the globe (Perkins et al. 2012; Tong et al. 2019). Although climate warming reduces the occurrence of extreme low temperature events, such as frost events, but the extension of the plant growing season due to warming may induce more frequent frost days during the growing season (Baumbach et al. 2017; Liu et al. 2018). Accompanied by changes in temperature, the adaptive capacity of vegetation to environmental changes and ecosystem vulnerability increases, significantly affecting the provision of global ecosystem services (Fu et al. 2013). Therefore, monitoring vegetation growth and understanding its response to temperature change is important for quantifying

global carbon budget, and has become a hot topic in climate change research (Ballantyne et al. 2012; Sitch et al. 2015).

Ecosystems in arid and semi-arid regions are more fragile to climate change due to harsh environmental condition, and even slight changes in the climate can have a substantial influence on such ecosystems (Li et al. 2021a; Yuan et al. 2021). However, previous studies on climate change have mainly focused on the analysis of statistical distributions of climate variables, such as mean, maximum, and minimum values, while neglecting their association with ecosystems (Franzke 2015; Jiang et al. 2017). Climate change affects vegetation growth primarily by altering some key bio-temperature thresholds, such as 0°C, 5°C, 10°C, and 20°C (Yang et al. 2019; Yin et al. 2017; Zhao and Wu 2016). These temperature indicators are closely related to the growth and distribution of vegetation, and its changes may lead to alteration in ecosystem structure and function (Dong et al. 2012; Qiu and Lu 1980; Xiao et al. 2020). Recent evidence has indicated that changes in bio-temperature thresholds altered vegetation productivity and modified vegetation seasonality by affecting the initiation, termination and performance of vegetation photosynthetic activity over the Northern Hemisphere land (Xu et al. 2013). Meanwhile, the Normalized Difference Vegetation Index (NDVI), as a typical remote sensing index for measuring the vegetation greenness, was widely used to characterize the response of vegetation growth to climate change (Jiang et al. 2017; Piao et al. 2011; Wang et al. 2011). In recent decades, numerous studies have indicated that variations in global temperature have greatly affected vegetation dynamics in drylands (Luo et al. 2020; Yao et al. 2018). Nevertheless, few studies were focused on the relationship between key bio-temperature thresholds and NDVI. A quantitative assessment of the effects of changes in key bio-temperature thresholds on NDVI will helpful for understanding the response mechanisms of dryland ecosystems to climate change.

The Great Lakes Region of Central Asia (GLRCA) is located hinterland of the Eurasian continent, far from the ocean, and covers five countries: Kazakhstan, Kyrgyzstan, Turkmenistan, Tajikistan, and Uzbekistan, which is the largest dryland area in the temperate zone of the Northern Hemisphere (Li et al. 2015a; Yao et al. 2017). Over the past 33 years, the GLRCA has experienced rapid warming of approximately 0.36°C–0.42°C, which was stronger than the global average temperature (Hu et al. 2014). Greater warming significantly affects the intensity and frequency of extreme temperatures in the GLRCA, with an overall trend of increased extreme high temperature events and decreased extreme low temperature events (Liu et al. 2021; Luo et al. 2020; Zhang et al. 2019). Arid and semi-arid regions are very sensitive to climate change due to their fragile ecosystems and limited resilience to climate change (Lioubimtseva and Henebry 2009). Temperature changes can be directly reflected in changes in vegetation growth (Luo et al. 2020; Wu et al. 2021). Zhou et al. (2015) found that the warming trend in the GLRCA initially enhanced the greenness of vegetation before 1991, but then the continued warming trend inhibited further increase in greenness. In addition, several studies have also demonstrated that the increase in temperature prolonged the growing season, and in turn increased ecosystem productivity in some areas of the GLRCA (Bohovic et al. 2016; Wu et al. 2021). However, it remained uncertain how key bio-temperature thresholds changed over the GLRCA, and different bio-temperature may induce various impacts on terrestrial

ecosystems under global warming. Therefore, it is essential to explore the spatial and temporal associations of vegetation growth and key bio-temperature thresholds in the GLRCA.

In this study, we selected the number of days with daily mean temperature above 0°C (DT_0), 5°C (DT_5), 10°C (DT_{10}), 20°C (DT_{20}), the start of growing season (SGS), the end of growing season (EGS), and the length of growing season (LGS) as key indicators of bioclimatology. Based on these indicators, we firstly investigated the temporal and spatial trends of bio-temperature in the GLRCA during the period 1982–2014. Secondly, Pearson's correlation coefficient was used to explore the correlation between NDVI and bio-temperature indicators, thus detecting the response of vegetation growth to temperature changes. This study provides a scientific basis for quantitative assessment of vegetation growth changes in dryland ecosystems under global warming, and will be helpful for decision-making in implementing ecological restoration and conservation in arid and semi-arid regions.

2. Data And Methods

2.1. Data

2.1.1. NDVI data

Remote sensing data, characterized by time continuity and large spatial scales, is an efficient approach to monitor the growth status and cover of vegetation (Goward 1989), and has been widely used in vegetation response to climate change studies (Li et al. 2015b; Wu et al. 2021). In this study, we used the Global Inventory Monitoring and Modeling Studies (GIMMS) NDVI dataset from 1982 to 2014 at a spatial resolution of 8 km × 8 km and a bimonthly time resolution. This dataset is corrected through a series of processing steps to reduce noise interference from volcanic eruptions and sensor-induced errors, with high quality. To characterize the yearly growth of vegetation, we used the maximum value composite (MVC) method to obtain the monthly NDVI dataset, and yearly NDVI was defined as the average monthly composite NDVI (Piao et al. 2011; Wang et al. 2011).

2.1.2. Climate data

The daily mean temperature data used in this study was obtained from the GLDAS-2.0 dataset provided by the Global Land Data Assimilation System (GLDAS), covering our study period (1982–2014), with a spatial resolution of 0.25 ° × 0.25 °. GLDAS combines simulation models with observations to provide long-term gridded meteorological datasets on a global scale, and has been widely used in climate change research (Ji et al. 2015; Wang et al. 2019; Zhong et al. 2011). Additionally, Ji et al. (2015) compared the GLDAS dataset with the Global Historical Climatology Network (GHCN) datasets (including 13511 weather stations), and found that the daily mean temperature data of GLDAS had a fairly high accuracy.

2.2. Methods

2.2.1. Bio-temperature indicators

Bio-temperature thresholds are closely related to the growth and distribution of vegetation, and 0°C, 5°C, 10°C, 20°C have been widely used to assess regional heat resources (Yang et al. 2019; Yin et al. 2017; Zhao and Wu 2016). 5°C is the minimum temperature for photosynthesis of some tropical and subtropical evergreen broadleaf forests (Larcher and Biederman-Thorson 1980). Meanwhile, 5°C was often employed to quantify growing season length and was also considered to be a key indicator in modelling of global vegetation patterns in previous studies (Prentice et al. 1992; Ruml et al. 2017). Most thermophilic crops begin to grow when the daily mean temperature is steadily above 10°C, and DT_{10} is closely associated with sprouting and withering of most arboreal leaves (Huang 1958; Qiu and Lu 1980). Furthermore, the number of days below 0°C (frost days) and DT_{20} are commonly used to characterize the variability of extreme temperature events (Sillmann et al. 2013; Xiao et al. 2020). To reduce the effect of extreme values, we employed a 6-day moving average as the daily mean temperature to calculate DT_0, DT_5, DT_{10} and DT_{20} in this study.

The effect of surface air temperature on vegetation growth is usually assessed by changes in the thermal growing season (Dong et al. 2012; Yin et al. 2019). Considering the heat requirements for most vegetation growth, the Expert Team on Climate Change Detection and Indices (ETCCDI) defined a set of growing season indicators based on daily mean temperature, and has been widely used in climate change studies (Cornes et al. 2019; Ruml et al. 2017). In the Northern Hemisphere, SGS was defined as the first day of the first 6-day period before July 1st with a daily mean temperature greater than 5°C, and EGS was determined as the first day of the first 6-day period after July 1st with a daily mean temperature less than 5°C. LGS was the number of days between SGS and EGS. Ultimately, seven bio-temperature indicators were selected in this study to analyze the effect of temperature change on vegetation growth across the GLRCA (Table 1).

Table 1
The bio-temperature indicators used in this study.

Label	Index Name	Unit
DT_0	Number of days with $T_{mean} > 0°C$	Days
DT_5	Number of days with $T_{mean} > 5°C$	Days
DT_{10}	Number of days with $T_{mean} > 10°C$	Days
DT_{20}	Number of days with $T_{mean} > 20°C$	Days
SGS	Start of growing season	Julian days
EGS	End of growing season	Julian days
LGS	Length of growing season	Days

2.2.2. Correlation analysis

To examine the response of vegetation dynamics to temperature changes, we analyzed correlations between annual NDVI and various bio-temperature indicators using Pearson's correlation coefficient based on pixels (Wu et al. 2021).

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

where r is the correlation coefficient between annual NDVI and climate indicator; x_i and y_i are annual NDVI and climate data for year i, respectively; and $\bar{x}$ and $\bar{y}$ are the mean of the annual NDVI and climate data over the entire study period, respectively. An r value less (greater) than 0 indicates a negative (positive) correlation. The greater the absolute value of r, the higher the correlation between annual NDVI and bio-temperature variables. A P value <0.05 for correlation analysis was considered statistically significant.

2.2.3. Trend Analysis and Mann–Kendall test

In this study, a linear regression, calculated by the least-squares method, was performed to detect trends in NDVI and climate variables. A positive slope indicates an increasing trend and a negative slope indicates a decreasing trend. In addition, the Mann-Kendall test was adopted to assess the reliability of time series trends (Kendall 1990; Mann 1945). This non-parametric test, which does not require the data to follow a standard distribution pattern and is not affected by sporadic outliers (Sneyers 1990), has been widely used to examine trends in hydrological and environmental data (Luo et al. 2020; Zhao and Wu 2016). In this study, a P value <0.05 was considered significant.

3. Results

3.1. Spatial and temporal variation of temperature and NDVI

Figure 1 illustrates the spatial patterns of trends in annual temperature, annual NDVI, and correlation between annual temperature and annual NDVI over the GLRCA for the period 1982–2014. During the entire study period, annual temperature exhibited an obvious increasing trend and had large spatially heterogeneity. Greater warming (> 0.035°C/yr) occurred mainly in the west and southeast. Meanwhile, approximately 63.8% of study area experienced a decreasing trend in annual NDVI. Spatially, the greater

decrease (< -0.0008 yr^{-1}) in annual NDVI was observed mainly in the west, and the greater increase (> 0.0008 yr^{-1}) was primarily in the east. To investigate the response of vegetation growth to temperature changes, we further analyzed the correlation between annual temperature and annual NDVI based on Pearson's correlation coefficient. From 1982 to 2014, approximately 56.4% of the study area was subject to a positive correlation between annual temperature and annual NDVI, and a greater positive correlation (> 0.2) was observed primarily at high altitudes in the southeast.

3.2. Spatial and temporal variation of DT_0, DT_5, DT_{10} and DT_{20}

To further explore the spatial and temporal variation in temperature, we analyzed the trends in DT_0, DT_5, DT_{10}, and DT_{20} over the GLRCA during 1982–2014. At the regional scale, DT_0, DT_5, DT_{10}, and DT_{20} exhibited an overall increasing trend at the rate of 0.505 days/yr, 0.503 days/yr, 0.454 days/yr, and 0.398 days/yr, respectively, and all passed the significance test at the 0.01 level (Figure 2). Spatially, the trends in DT_0, DT_5, DT_{10}, and DT_{20} were obviously heterogeneous over the entire study area (Figure 3). The most pronounced increase (> 0.6 days/yr) in DT_0 was primarily observed in the west and the southeast, accounting for about 28.1% of the study area. Meanwhile, approximately 31.8% of the study area experienced a greater increase (> 0.6 days/yr) in DT_5, and occurred mainly in the central and southeast. For DT_{10}, the greater increase (> 0.6 days/yr) was observed mostly in the south, accounting for 22.1% of the study area. About 23.1% of the study area showed a larger increase (> 0.6 days/yr) in DT_{20}, occurring mainly in the west and south. In addition, a clearly decreasing trend in DT_{20} was observed in the northeast, accounting for approximately 10.0% of the study area.

To further explore the effect of temperature change on vegetation growth, we analyzed the correlation of annual NDVI with DT_0, DT_5, DT_{10}, and DT_{20} across GLRCA for the period 1982–2014 (Figure 4). Spatially, there was a clear heterogeneity in the correlation between the annual NDVI and the four bio-temperature indicators. From 1982 to 2014, positive correlations between annual NDVI with DT_0, DT_5 occurred in 54.8%, 46.0% of the study area, respectively, and greater positive correlations (> 0.30) were observed mainly at high elevations in the southeast. Meanwhile, about 66.7% of study area was subject to a negative correlation between the annual NDVI and the DT_{10}, especially in the central region with a greater negative correlation (< -0.30). Furthermore, most of the study area (approximately 88.3%) experienced a negative correlation between annual NDVI and DT_{20}, and the greater negative correlation (< -0.30) was widely distributed in the west. Overall, the larger the number of days with higher temperature, the greater the negative impact on vegetation growth.

3.3. Spatial and temporal variation of SGS, EGS and LGS

Based on daily mean temperature data in the GLRCA during 1982–2014, we further calculated three bio-temperature indicators: SGS, EGS, and LGS. Figure 5 illustrates the interannual trends in SGS, EGS, and LGS at the regional scale in the GLRCA. During the entire study period, SGS exhibited a slight decreasing

trend with a regional average rate of -0.040 days/yr. Meanwhile, EGS showed a pronounced increasing trend at a rate of 0.460 days/year, and passed the significance test at 0.01 level. Changes in LGS are controlled by changes in SGS and EGS. We further analyzed the interannual trend in LGS and found that LGS across the GLRCA increased at a rate of 0.500 days/yr ($P < 0.01$) at the regional scale.

Figure 6 indicates the spatial distribution of trends in SGS, EGS, and LGS over the GLRCA during the period 1982–2014. Over the past 33 years, most of the study area (about 67.8%) exhibited a negative trend in SGS. Spatially, the greater advanced SGS (< -0.4 days/yr) was mainly observed in the south, while the delayed SGS was mostly in the north. For trends in EGS, more than 99.0% of the study area experienced an increasing trend. The larger delays in EGS occurred mainly in the central and southeast. Accompanied by an earlier SGS and a later EGS, LGS showed a pronounced positive trend over 98.1% of the study area, and a higher extended SGS was observed mainly in the central and south.

Temperature is one of the major drivers of vegetation phenology changes. Therefore, we analyzed the correlations between annual NDVI and three indicators of growing season (SGS, EGS, and LGS) derived from surface air temperature to identify the impact of growing season variability on vegetation dynamics (Figure 7). Over the whole study period, the regions showing a negative correlation between annual NDVI and SGS accounted for about 66.7% of the study area, and the greater negative correlation (< -0.2) occurred mainly in the north and southeast. Meanwhile, approximately 64.1% of the study area experienced a negative correlation between annual NDVI and EGS, and a larger negative correlation (< -0.2) was observed mostly in the north. Then, we analyzed the correlation between annual NDVI and LGS, and found that a negative correlation represented approximately 54.7% of the study area. Spatially, the greater negative correlation (< -0.2) between annual NDVI and LGS was mainly found in the central, and the larger positive correlation (> 0.2) was mainly in the southeast.

4. Discussion

In this study, we investigated the spatial and temporal variation of bio-temperature indicators (including DT_0, DT_5, DT_{10}, DT_{20}, SGS, EGS, and LGS), and further analyzed the response of vegetation growth to changes in bio-temperature indicators across the GLRCA for the period 1982–2014.

Over the entire study period, GLRCA experienced a significant warming trend, and such climate warming has induced a series of ecological and environmental effects (Liu et al. 2019; Yu et al. 2021). Since the 1970s, nearly half the great lakes in the GLRCA have shrunk, and considerable glaciers are rapidly retreating due to climate warming (Yu et al. 2021). In the present study, a significant decreasing trend in annual NDVI was observed in most of the study area (63.8%), especially around the Aral Sea, while a significant increasing trend was mainly in the east. This variation in vegetation dynamics was also identified in previous studies (Jiang et al. 2017; Zhang et al. 2018). Meanwhile, numerous studies have suggested that temperature played a major role in the vegetation dynamics across the GLRCA (Jiang et al. 2017; Luo et al. 2020).

During 1982–2014, over 56.4% of the study area experienced a positive correlation between annual temperature and annual NDVI, particularly at high altitudes in the southeast. Generally, at high altitudes, temperature is the dominant climatic factor affecting vegetation growth (Wang et al. 2014; Wang et al. 2021). Thus, the increase in vegetation greenness in the mountainous of the GLRCA could be attributed to climate warming (Jiang et al. 2017; Zhou et al. 2015). However, rapid warming could significantly increase evapotranspiration and lead to soil moisture deficit, which in turn limit vegetation growth (Anderegg et al. 2013; Zhang et al. 2021). This might explain the negative correlation of annual NDVI with annual temperature in the west of the study area.

Climate change manifests itself not only as changes in mean conditions, but also as changes in some key bio-temperature thresholds (Zhao and Wu 2016). Key bio-temperature are closely related to the growth of vegetation, and slight changes could produce substantial effects on the structure and function of ecosystems (Yang et al. 2019; Yin et al. 2019). Therefore, we further analyzed the spatial and temporal trends in DT_0, DT_5, DT_{10}, and DT_{20}. Overall, four indicators showed a pronounced increasing trend, which is the consequence of increased temperature in the GLRCA (Feng et al. 2018). Spatially, this increase has significant variability, which should be strongly associated with the spatial and temporal heterogeneity in surface characteristics, such as topography and urbanization (Toelle and Churiulin 2021). Moreover, a clearly decreasing trend in DT_{20} was observed in the northeast, and Figure 1 (a) reveals that the annual mean temperature in the region also insignificantly increased during 1982–2014. Previous studies found that increased precipitation and vegetation greening could induce a cooling effect on regional temperatures (Barbero et al. 2018; Yuan et al. 2017). Therefore, the increase in precipitation and NDVI over the northeastern GLRCA should contribute to the decrease in DT_{20} (Jiang et al. 2017).

For the period 1982–2014, the correlations of annual NDVI with DT_0, DT_5, DT_{10}, and DT_{20} showed obviously spatially heterogeneous. It implied that the response of vegetation dynamics to temperature drivers was highly variable due to different vegetation characteristics and environmental conditions (Li et al. 2021b; Luo et al. 2020). A slight increase in temperature would exert a positive impact on regional vegetation growth by reducing frost days and extending the growing season (Wu et al. 2021; Zhao et al. 2021). At the same time, a significant positive correlation between annual NDVI and temperature indicators was observed at high elevations in the southeast because cold temperature is a serious constraint to vegetation growth in the region (Jiang et al. 2017). However, most of the regions in GLRCA showed that the negative correlation between DT_0, DT_5, DT_{10}, DT_{20} with annual NDVI increased with increasing bio-temperature thresholds, which may be due to increased temperature intensifying precipitation limitation for dryland vegetation growth (Wu et al. 2019; Zhang et al. 2016). Especially, more than 88.3% of the study area showed a negative correlation between annual NDVI and DT_{20}. In general, DT_{20} occurred mainly in summer, and high temperatures could further increase ecosystem drought. Recently, the negative effects of high temperatures on ecosystems have been widely reported in many regions, especially in arid and semi-arid areas (Baumbach et al. 2017; Li et al. 2021b). Under high temperature stress, vegetation photosynthesis is weakened or even stalled, while respiration is enhanced, thus leading to a decrease in productivity (Salvucci and Crafts-Brandner 2004; von Buttlar et al. 2018).

Vegetation phenology, including SGS, EGS, and LGS, is a sensitive signal indicating the response of vegetation dynamics to climate change (Richardson et al. 2012; Wu et al. 2021). Plenty of remote sensing data and ground observation data demonstrated that spring phenology has advanced and fall phenology has delayed owing to global warming (Dong et al. 2012; Sun et al. 2020; Wu et al. 2021). In this study, LGS presented a significant positive trend at a rate 0.500 days/yr for the regional scale, and delayed EGS (0.460 days/year) contributed greater relative to advanced SGS (-0.040 days/yr). This result is consistent with other studies around the globe (Dong et al. 2012; Sun et al. 2020). Spatially, a pronounced delay in SGS was observed in the north. In fact, spring cooling has been noted in some regions of the Northern Hemisphere over the last decades (Sun et al. 2019; Wang et al. 2011). Such a spring cooling could possibly result in delayed SGS in the GLRCA. In addition, the spatial pattern of LGS was similar to that of DT_5 because the growing season in this study was defined based on 5°C and DT_5 in a year occurred mostly within the growing season.

Environmental changes are inconsistent with the vegetation response, which may lead to different trends in growing season derived from surface air temperature and growing season based on actual vegetation phenology (Sun et al. 2020; Wu et al. 2021). Therefore, we further analyzed the correlations between annual NDVI with SGS, EGS, and LGS. Generally, prolonged LGS controlled by advanced SGS and delayed EGS can increase the time of material accumulation, thereby enhancing vegetation productivity (Piao et al. 2007; Richardson et al. 2010). Meanwhile, a pronounced positive correlation between annual NDVI and LGS was observed at high elevations in the southeast. Furthermore, our study found that annual NDVI was negatively correlated with LGS in some regions of the GLRCA, especially in the north. In dryland ecosystems, precipitation is the major driver of vegetation greening, and increased evapotranspiration controlled by climate warming would lead to drought and exacerbate precipitation limitation (Ma et al. 2015). In addition, the increase in temperature might accelerate the growth of vegetation and thus lead to a shortening of the vegetation growth cycle, particularly for herbaceous plants (Sherry et al. 2007; Wu et al. 2021). Hence, these could explain the negative effect of extended LGS on vegetation growth across the GLRCA.

5. Conclusions

This study analyzed the temporal and spatial characteristics of bio-temperature indicators (DT_0, DT_5, DT_{10}, DT_{20}, SGS, EGS, and LGS) in the GLRCA based on surface air temperature data during 1982–2014, and examined the response of vegetation dynamics to climate change. The major findings are as follows.

(1) With climate warming, DT_0, DT_5, DT_{10}, and DT_{20} all showed a pronounced increasing trend at the regional scale. Spatially, there was significant heterogeneity in the four indicators, particularly an obvious decrease in DT_{20} was observed in the northeast.

(2) Most of the study area showed that the negative correlation between DT_0, DT_5, DT_{10}, DT_{20} with annual NDVI increased with increasing bio-temperature thresholds. Especially, more than 88.3% of the study area experienced a negative correlation between annual NDVI and DT_{20}.

(3) During the entire study period, SGS exhibited insignificantly advanced trend, and EGS experienced a significantly delayed trend. Therefore, the overall extending trend in LGS was mainly attributed to the delayed EGS.

(4) About 54.7% of the study area showed a negative correlation between annual NDVI and LGS due to precipitation limitation exacerbated by climate warming, especially in the north, indicating a negative effect of climate warming on dryland vegetation growth.

Declarations

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

Xuan Gao and Lei Liu analyzed the data and wrote the manuscript. Dongsheng Zhao provided guidance and revised the manuscript.

Data Availability

Meteorological data supporting this research are openly available at https://disc.gsfc.nasa.gov/.

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Figures

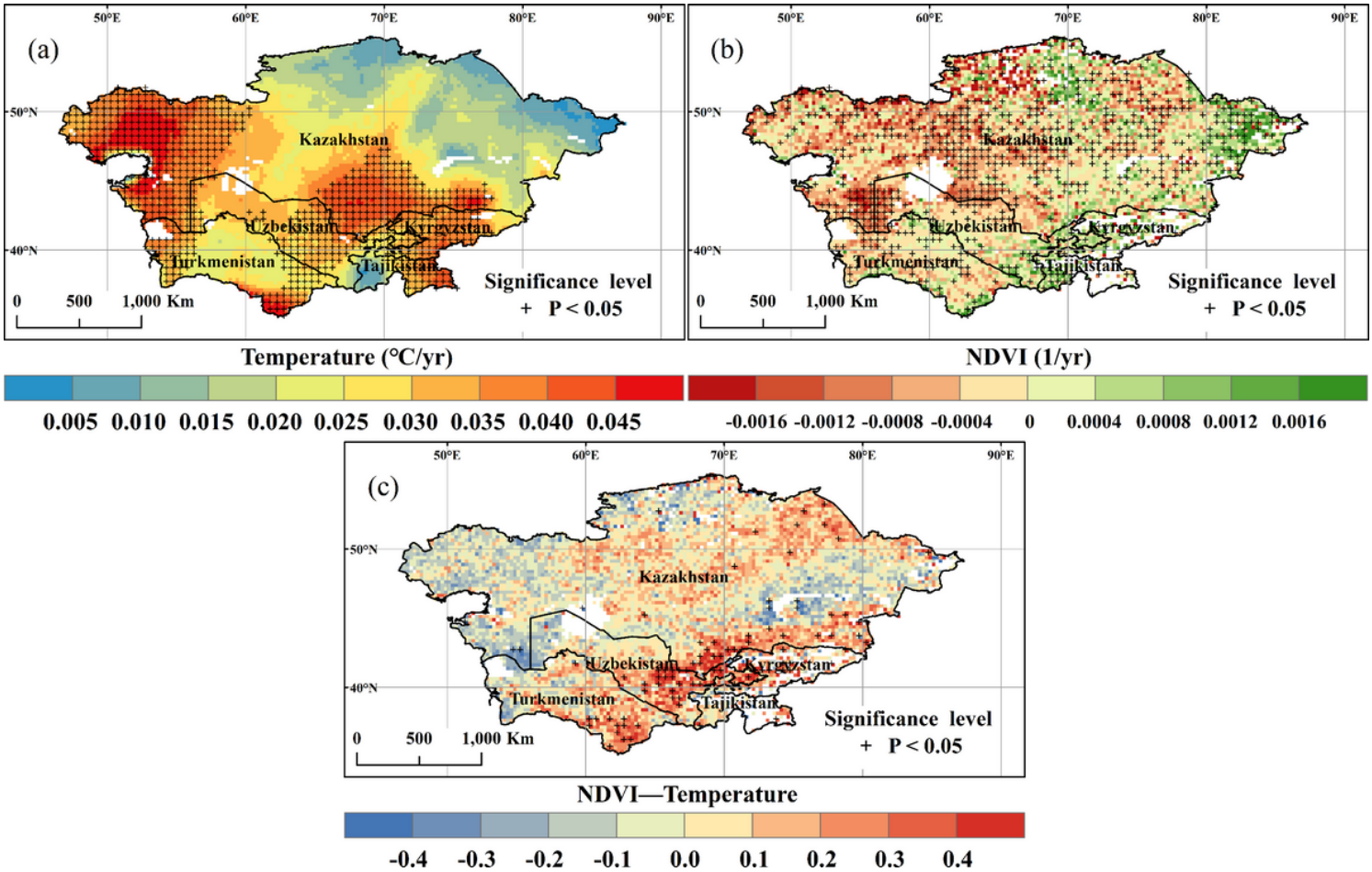

Figure 1

Spatial distribution of trends in (a) annual temperature, (b) annual NDVI, and (c) correlation between annual temperature and annual NDVI over the GLRCA during 1982–2014.

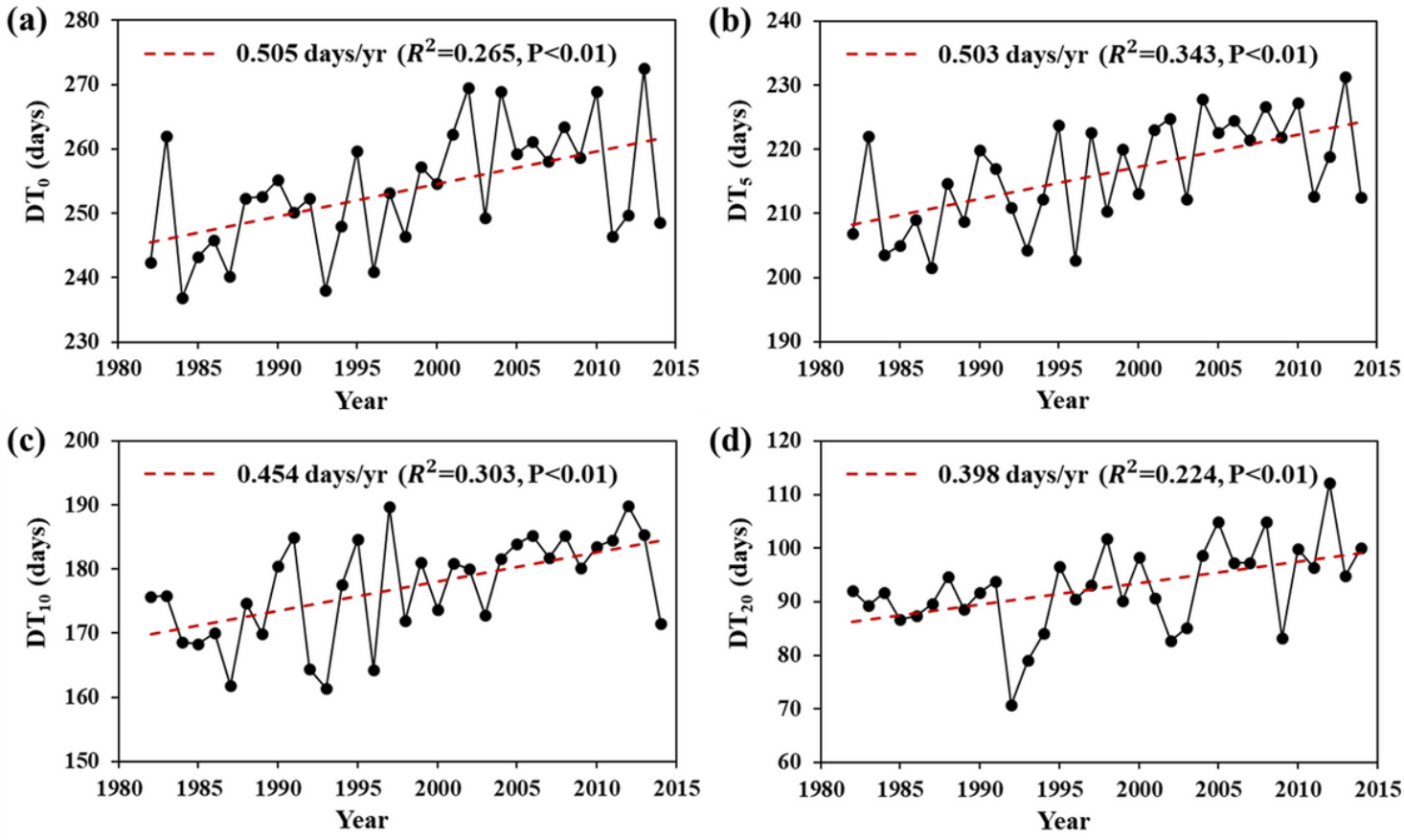

Figure 2

Interannual variations in (a) DT_0, (b) DT_5, (c)DT_{10}, and (d) DT_{20} at a regional scale in the GLRCA during the period 1982–2014.

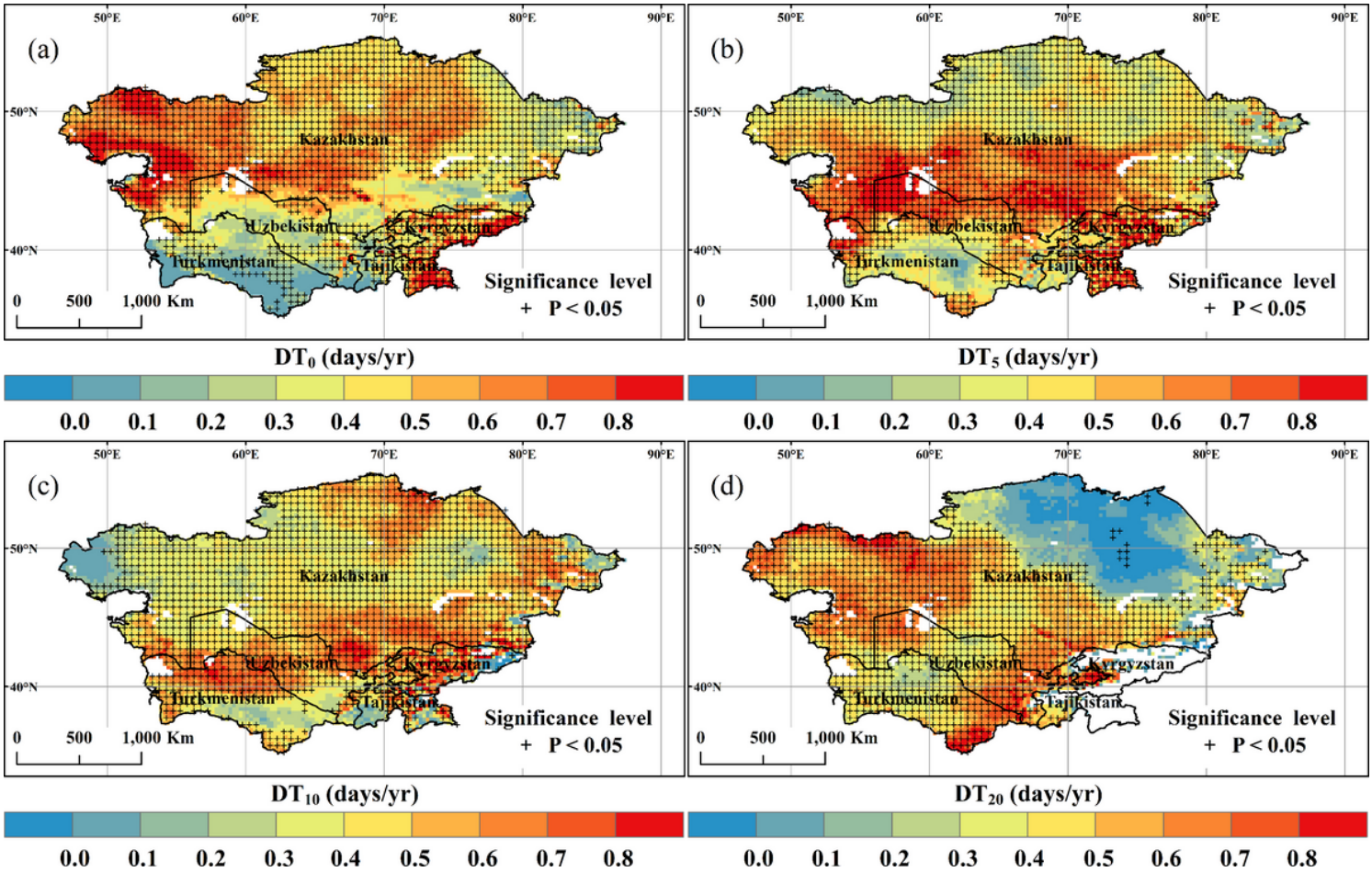

Figure 3

Spatial distribution of trends in (a) DT_0, (b) DT_5, (c)DT_{10}, and (d) DT_{20} during the period 1982–2014.

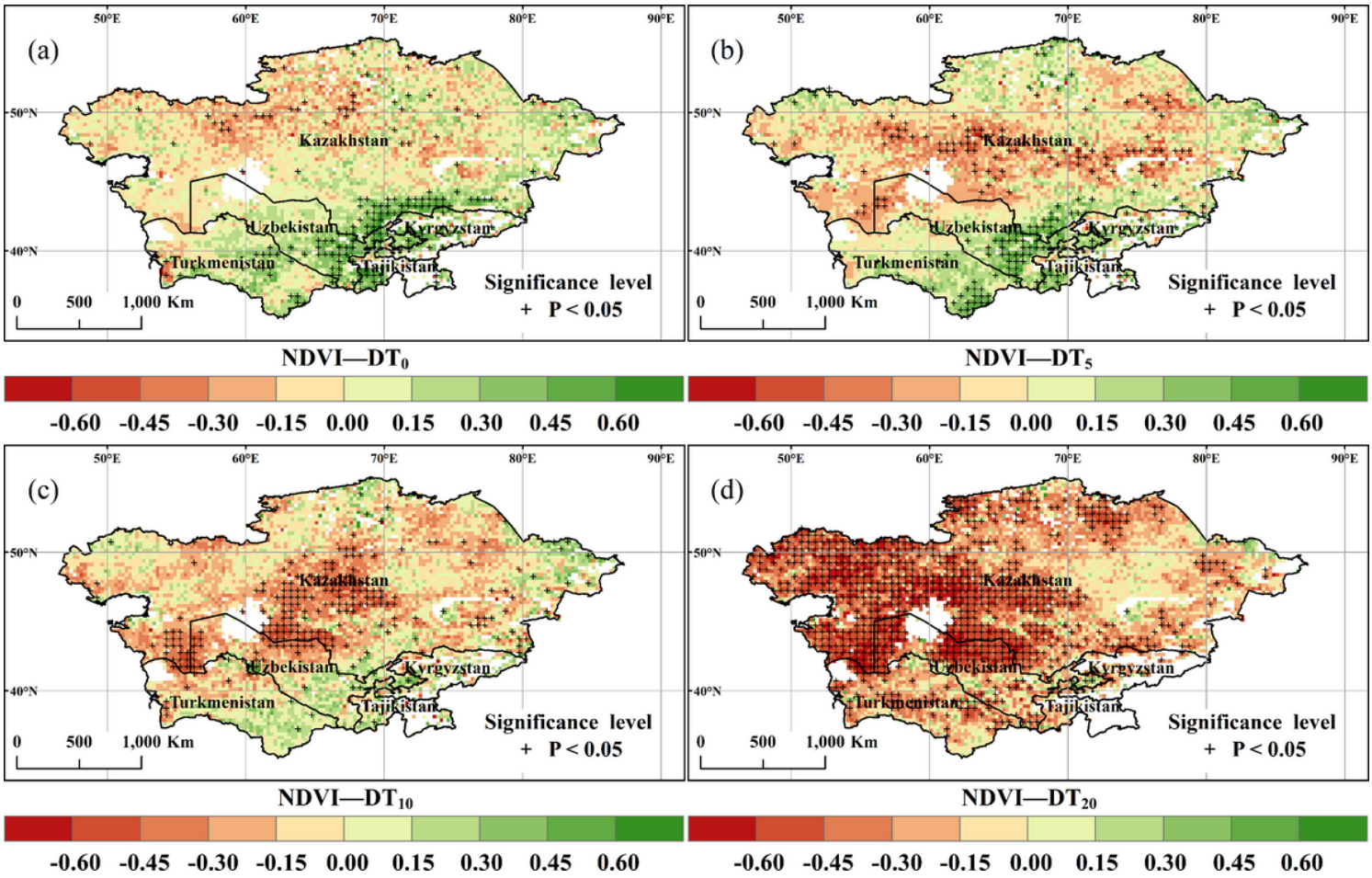

Figure 4

Spatial distribution of correlations between annual NDVI and (a) DT_0, (b) DT_5, (c) DT_{10}, and (d) DT_{20} for the period 1982–2014.

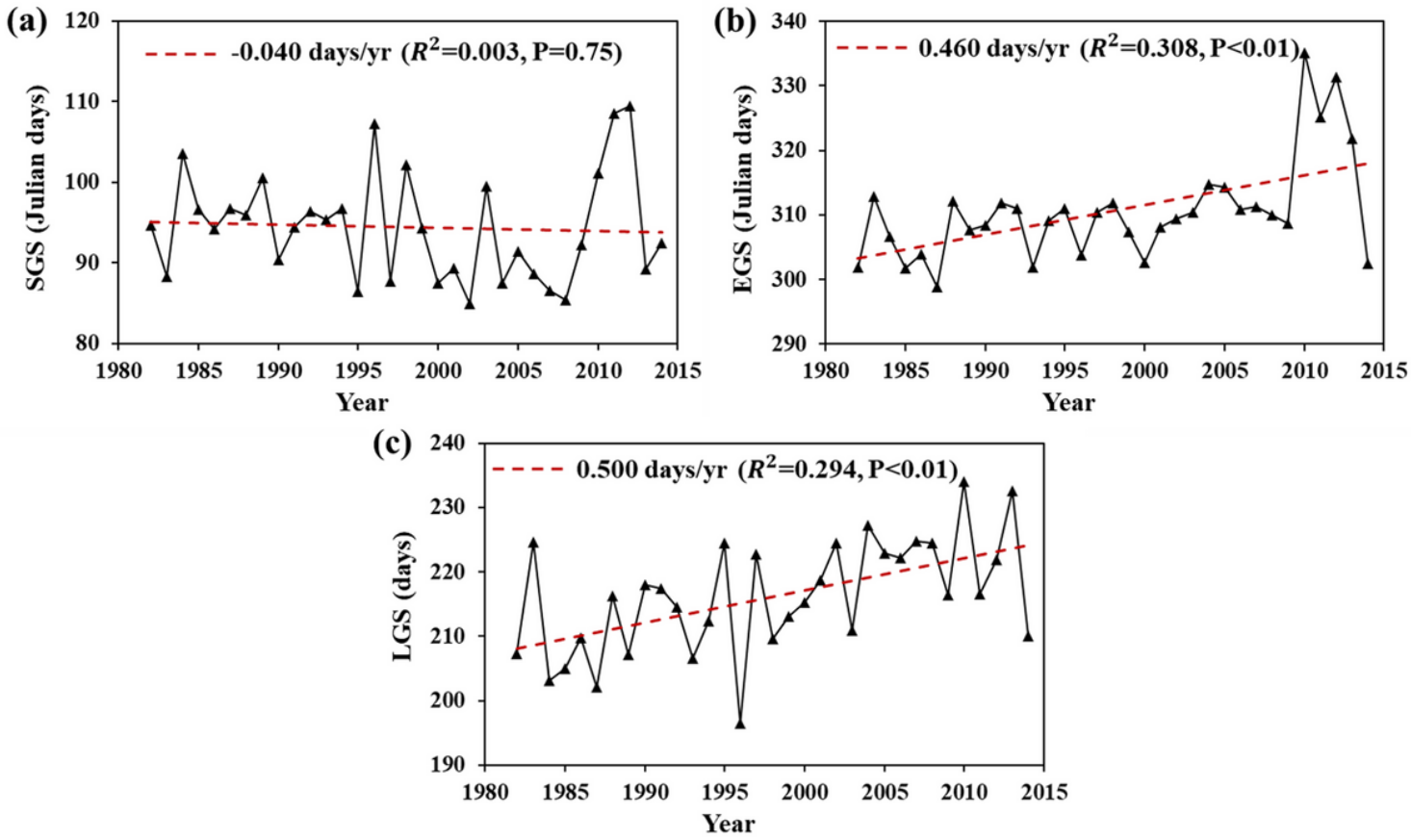

Figure 5

Interannual variations in (a) SGS, (b) EGS, and (c) LGS at a regional scale in the GLRCA during the period 1982–2014.

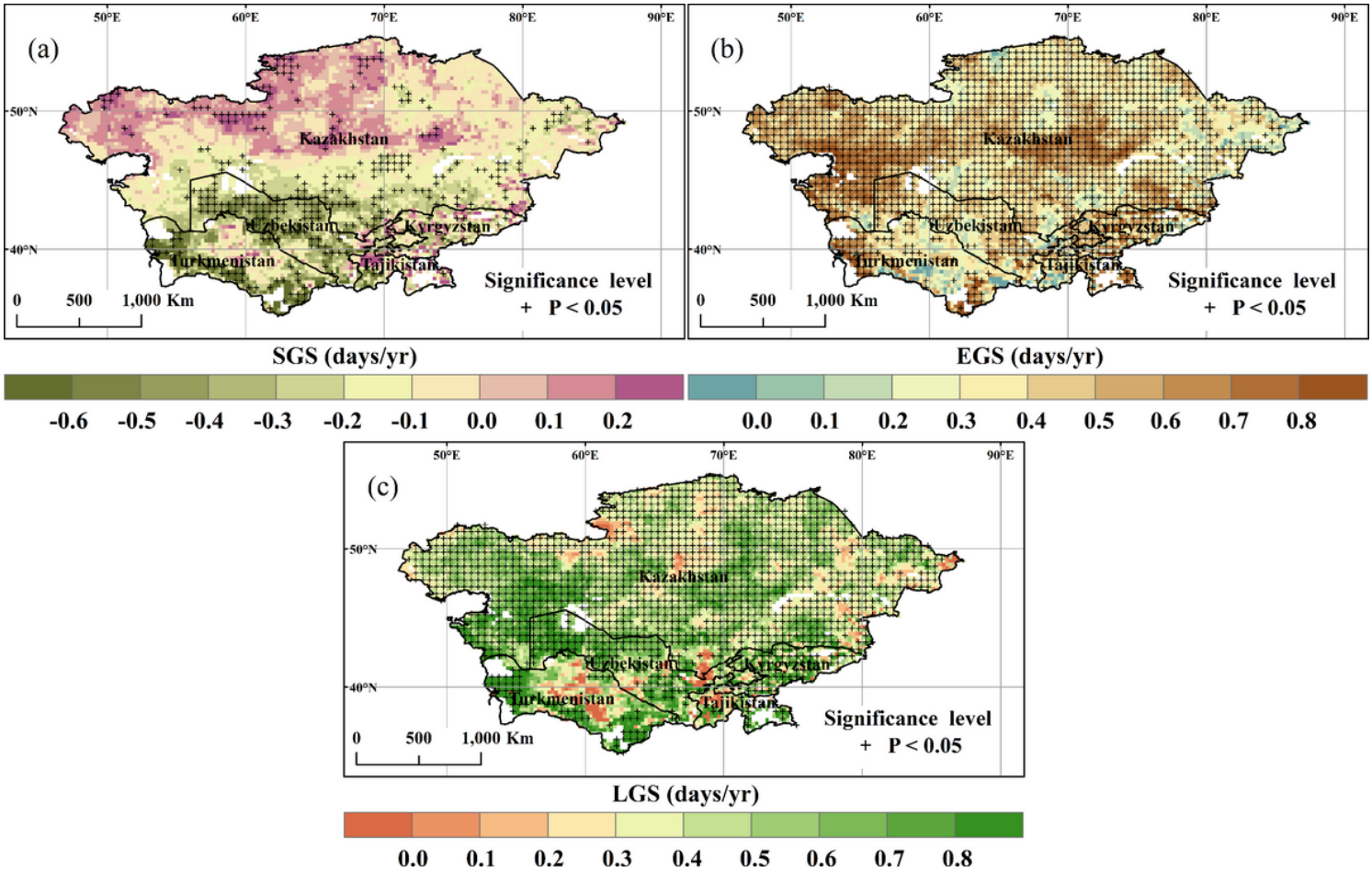

Figure 6

Spatial distribution of trends in (a) SGS, (b) EGS, and (c) LGS for the period 1982–2014.

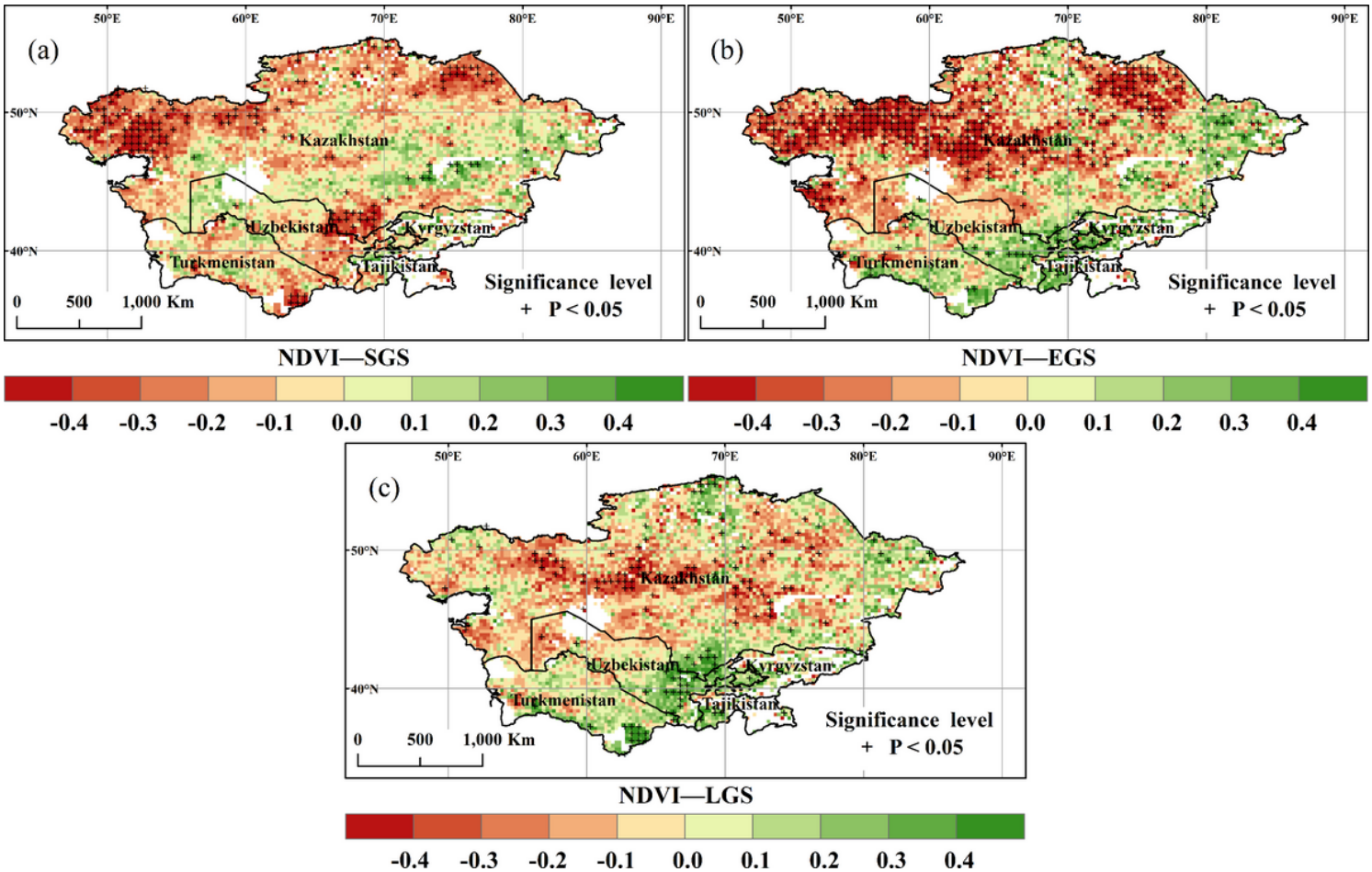

Figure 7

Spatial distribution of correlations between annual NDVI and (a) SGS, (b) EGS, and (c) LGS during 1982–2014.