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Pattern and change of NDVI and their environmental influencing factors for 1986–2019 in the Qinling-Daba Mountains of central China

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Previous studies have shown that climate change and human activities play an important role in the vegetation dynamics in the Qinling-Daba Mountains of central China. However, which environmental factors including climate, topography, soil and human activities play an important role in the vegetation dynamics and its spatial pattern in the Qinling-Daba Mountains remains to be further clarified. Based on the normalized difference vegetation index (NDVI) data of the growing season from 1986 to 2019 synthesized by Landsat series satellite data on Google Earth Engine, this study aimed to further investigate the spatial pattern of NDVI and its dynamics, and clarify its environmental controlling factors in the Qinling-Daba Mountains using the methods of spatial analysis and Geodetector. The results showed that: (1) the spatial pattern of NDVI in the study area had a U-shaped NDVI distribution in latitude, anti-U-shaped patterns in longitude and with increasing altitude. (2) 2005 was the year of NDVI breakthrough increase, and the vegetation dynamics was divided into two periods according to the result of MK mutation test: the slow increasing period with an increasing rate of 0.25%/a from 1986 to 2004 (R^2 0.74), and the rapid increasing period with an increasing rate of 0.30%/a from 2005 to 2019 (R^2 0.92). (3) Topography regulating local hydrothermal conditions and soil enriching nutritions played more important influence on NDVI spatial pattern than climate factors (temperature and precipitation) at the regional scale. The effect of land use on NDVI change was stronger than that of climate warming (temperature), and the climate warming in recent decades played a more important role than precipitation on the NDVI dynamics. Research on vegetation patterns, changes and their environmental influencing factors will help the government and other related agencies to formulate plans or policies for infrastructure development and land management, ecological restoration.

KEYWORDS
Qinling-Daba Mountains, normalized difference vegetation index, climate warming, land use, topography

1 Introduction

Vegetation as an important part of the terrestrial ecosystem (Piao et al., 2003), has a significant influence on global material and energy flows, carbon balance and climate stability at different temporal and spatial scales (Schimel et al., 2000; Albani et al., 2006; Liu and Lei, 2015; Ren and Li, 2003). Due to its high sensitivity to environmental changes, vegetation dynamics has been recognized as an important indicator for monitoring the climate change (Parmesan and Yohe, 2003; Zhang and Li, 2023). Many studies on vegetation dynamics have used Normalized Difference Vegetation Index (NDVI) as an indicator to analyze the characteristics, dynamics and driving factors of vegetation (Fang et al., 2003; Anyamba and Tucker, 2005; Jong et al., 2011; Wang J. et al., 2019; Wang W. et al., 2019). Earlier studies paid more attention to the relationship between climate change and vegetation change and found that climate change was the main driving factor of vegetation dynamics (Anyamba and Tucker, 2005; Liu et al., 2015; Phillips et al., 2008; Hussain et al., 2023). Recent studies have focused on the impacts of both human activities and climate change on vegetation dynamics, and the results suggest that human activities have both positive and negative impacts on vegetation change. The negative impacts of human activities on vegetation dynamics are mainly caused by the destruction and reduction in vegetation due to the infrastructure and commercial construction (Hussain et al., 2022; Deng et al., 2018) or urbanization (Yao and Cui, 2022). Some human activities such as land use management or ecological restoration projects, have positively contributed to the increase in NDVI (Chen et al., 2019a,b; Qu et al., 2020; Jiang et al., 2021; Xu et al., 2021; Yao and Cui, 2022).

Regional NDVI change and its response to climate warming and human activities are still hot topics in current studies of global environmental change (Xu et al., 2021; Ma et al., 2012). The Qinling-Daba Mountains known as the north–south transitional zone of China and a large east–west ecological corridor (Zhang, 2019; Yu et al., 2022), is a sensitive and important region for climate change (Luo, 2009) and human activities (Yao and Cui, 2022). And the vegetation of the Qinling-Daba Mountains has also undergone profound changes under the interaction of the climate warming and human activities (Yao and Cui, 2022; Li et al., 2022). Many studies analyzed the vegetation dynamics and its driving forces in the Qinling-Daba Mountains by NDVI and found that the NDVI showed a significant upward trend and the vegetation change was sensitive to temperature (Zhang et al., 2011; He et al., 2011; Ren et al., 2012; Cui et al., 2012; Chen et al., 2019a,b). However, some studies found that the NDVI change in the Qinling-Daba Mountains was due to the precipitation deficit (Liu et al., 2015). Some other studies found that the NDVI in the Qinling Mountains had a decreasing trend (Sun et al., 2010; Sun et al., 2009). The above studies, which used different source or temporal data and methods in different local study areas (covering parts of the Qinling-Daba Mountains such as Taibai Mountain or Micang Mountain), led to different conclusions. And they mainly focused on the trend of vegetation dynamics, and few of them discussed the spatial pattern of NDVI and its controlling factors at the regional scale.

Human activities have been shown to play an important role in climate and land surface changes (Stott et al., 2004; Wang et al., 2023). As an important composition of the land surface environment, vegetation dynamics is mainly related to topography, soil, climate conditions and human activities (Nemani et al., 2003; Xu, 2018). Recent studies have paid more attention to the effects of human activities and climate warming on vegetation dynamics. Cui et al. (2012) analyzed the response of vegetation to temperature and the distance from human aggregation areas in the Qinling Mountains from 2000 to 2009 based on MODIS NDVI data by linear regression and correlation analysis, and found that the temporal stability of vegetation was inversely distributed with the distance from human aggregation areas. Deng et al. (2018) pointed out that human activities had both positive (through the implementation of ecological restoration projects) and negative (through urbanization) effects on vegetation change. Yao and Cui (2022) analyzed the trend of NDVI change and its spatial variation with elevation, slope, and land use type based on annual growing season NDVI data from 1990 to 2019, and discussed the effects of climate warming and land use on vegetation dynamics. Although these studies discovered the increasing trend of NDVI values in Qinling-Daba Mountains in recent decades, and discussed the driving factors of climate change (temperature and precipitation) and human activities (land use), there is no further statement on which factor of them (climate change and human activities) plays more important roles on the vegetation dynamics in recent years. As we know, climate factors (temperature and precipitation) are the main controlling factors of vegetation distribution, while according to our field surveys and related studies, topography and soil in the Qinling-Daba Mountains have also significantly affected the NDVI pattern. But few studies have discussed the effects of topography and soils on regional NDVI patterns.

In a word, the spatial pattern of NDVI and its environmental influencing factors in the Qinling-Daba Mountains of central China need to be further investigated. Therefore, the objectives of this study are to further clarify: (1) the spatial pattern of NDVI and its environmental influencing factors in the study area; (2) which factor among these environmental factors plays a more important role in NDVI change in this region. Therefore, the environmental factors including climate, soil and topography are selected in this study to discover the influencing factor of NDVI pattern, and the factors including climate, population density, gross domestic product (GDP) and land use are selected as the influencing factors of NDVI change. The results of this study are of great significance for a comprehensive understanding of the impact of environmental factors, including climate warming and human activities, on the vegetation of the Qinling-Daba Mountains.

2 Datasets and methods

2.1 Study area

The Qinling-Daba Mountains, composed of the Qinling Mountains in the north, the Hanzhong Basin-Hanshui Valley in the middle, and the Daba Mountain in the south, is situated in central China (102°–114°E, 30°–36°N), covering a total area of about $30.60 \times 10^4\,km^2$ (Qin et al., 2008), and is known as the transitional zone of China (Kou et al., 2020; Yao et al., 2020) (Figure 1). It extends 1,000 km in the east–west direction and 200–300 km in the south–north direction, covering 155 counties, 31 cities and 6 provinces in central China (Figure 1). As the north–south transitional zone in China, steep elevation gradients and complex climate make it a biodiversity hotspot, the vegetation in this region gradually changes from subtropical evergreen broadleaf forest to deciduous broadleaf forest from south to north, and has vertical zonality in the mountains (Liu and Lu, 1990); it is also an important habitat for rare animals, containing many nature reserves and national parks (Yu et al., 2022). Therefore, this area is one of the most important and concerned areas for biodiversity in China, and one of the most sensitive areas to climate change and human activities (Yao and Cui, 2022; Zhang et al., 2019).

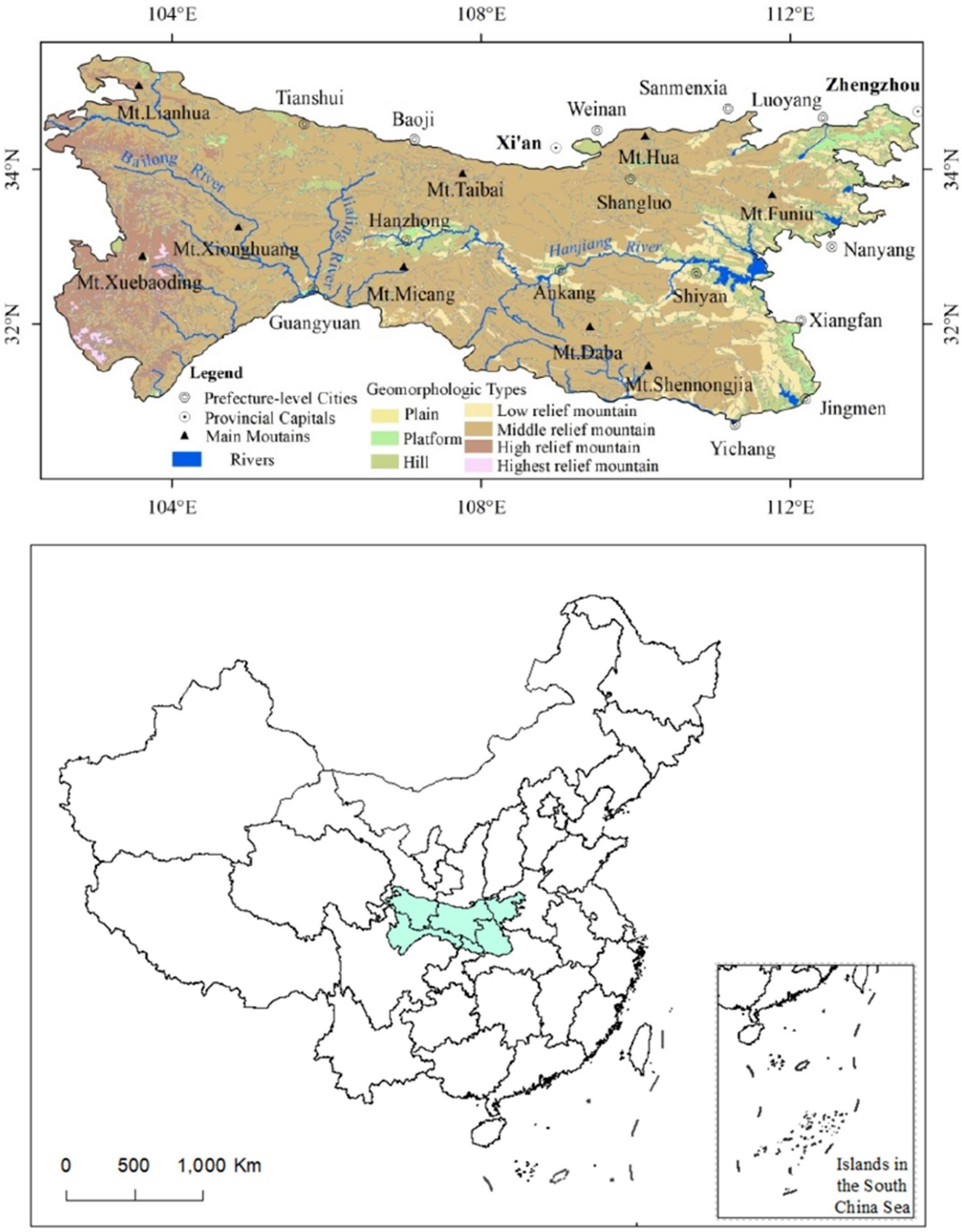

FIGURE 1
Location and geomorphological map of the Qinling-Daba Mountains in central China.

2.2 Datasets

The NDVI dataset used in this study was the annual growing season (May to September) NDVI data (30 m resolution) of Landsat 5/ Landsat 7/ Landsat 8 from 1986 to 2019, which were synthesized using the maximum synthesis method on the Google Earth Engine (GEE) platform. Savitzky–Golay (SG) filtering was applied to the annual growing season NDVI data to further reduce the noise (Kou, 2021). Temperature and precipitation data with 500 m resolution were downloaded from the Data Center of Resources and Environment Science, Chinese Academy of Sciences[1] for 1980–2015, which were generated by 2,400 meteorological stations using the spatial interpolation method (Figures 2A,B). The ASTER GDEM (Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model, downloaded from https://earthdata.nasa.gov/) with 30 m resolution was mainly used to analyze the pattern and change of NDVI with variable altitude. Land cover data sets (1 km

1 http://www.resdc.cn

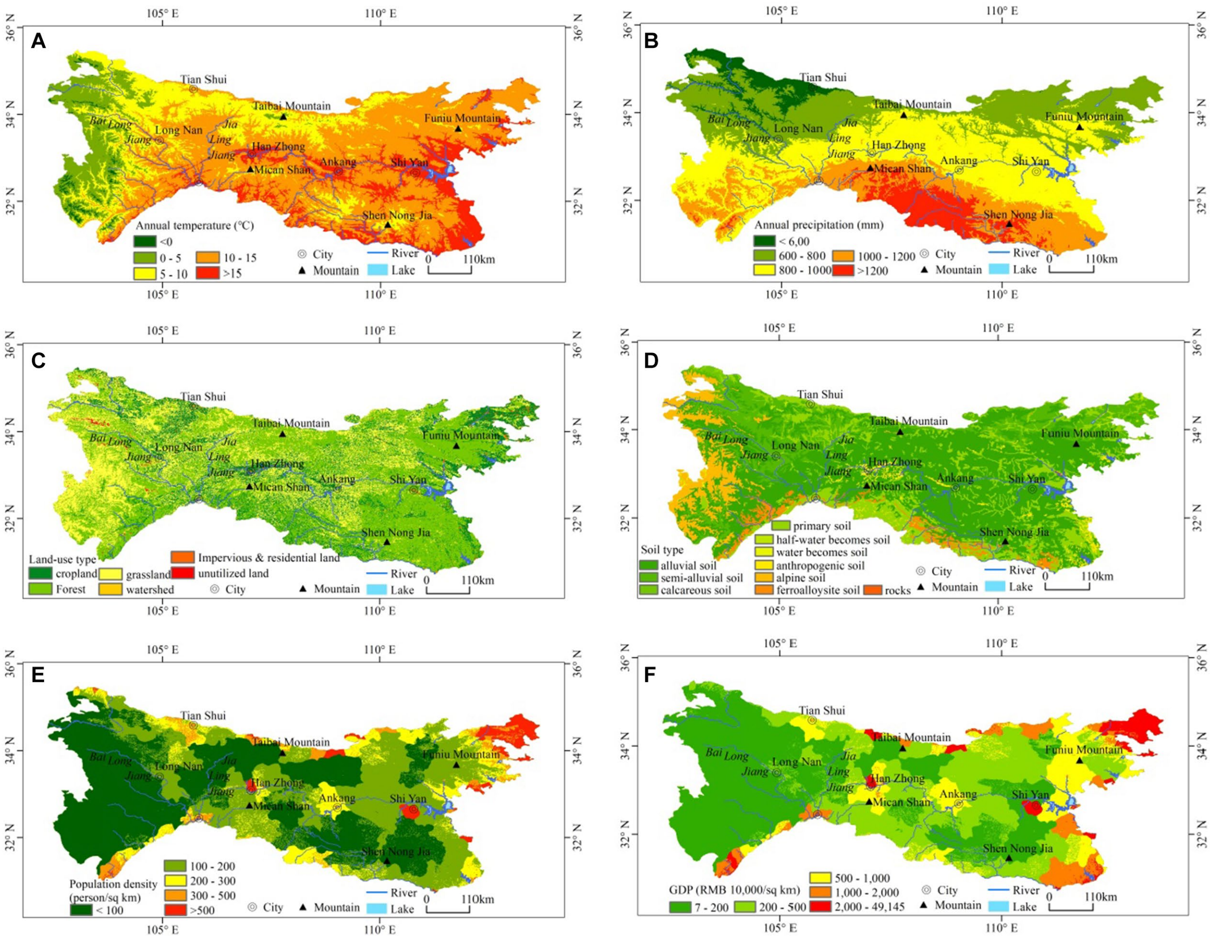

FIGURE 2
Main data and maps used in this study [**(A)** annual temperature; **(B)** annual precipitation; **(C)** land cover and land use in 2015; **(D)** soil map; **(E)** population density in 2015; **(F)** GDP in 2015].

resolution) for 1990, 1995, 2000, 2005, 2010 and 2015 were downloaded from the Data Center of Resources and Environment Science, Chinese Academy of Sciences (see text footnote 1) (Figure 2C). The soil type data (Figure 2D), population density (1990–2015), and GDP data (1995–2015) (all with 1 km resolution) were also downloaded from the Data Center of Resources and Environment Science, Chinese Academy of Sciences (see text footnote 1). Among of them, the soil type data were digitally generated according to the "1: 1,000,000 Soil Map of the People's Republic of China" compiled and published by the National Soil Census Office in 1995 (Figure 2D); the population density data and GDP data were based on the statistics of population and GDP by county, using the multi-factor weight distribution method to calculate the distribution weights of land use type, night light brightness, residential area density, and other related factors (Xu and Zhang, 2017) (Figures 2E,F). These data were used to analyze the influencing factors on NDVI pattern and change.

2.3 Methods

Firstly, the spatial patterns and dynamics of NDVI were analyzed. The Sen trend method (Sen, 1968) and Mann-Kendall (MK) significant test were used to analyze the NDVI trend for 1986–2019. The Sen trend method can effectively avoid the influence of time series data loss and data distribution form, and eliminate the interference of time series outliers (Liu et al., 2010), and the MK significant test (Mann, 1945; Kendall, 1975) was conducted to test the significance of the calculated Sen trend. The MK mutation test (Karpouzos et al., 2010) was used to determine the mutated NDVI change period and to discover the dynamic process of NDVI. The spatial patterns of NDVI along latitude, longitude and elevation in the Qinling-Daba Mountains were investigated by profile analysis (along 33.6° N and 107° E) and statistical analysis methods.

Then, the main environmental influencing factors of NDVI pattern and its change were investigated by Geodetector analysis. As we know, climatic factors such as temperature, precipitation, light and seasonal variation are the main factors influencing vegetation distribution, and soil factors such as soil type, texture, pH, and nutrient content have important effects on vegetation growth (Brady and Weil, 2008; Marschner, 2012). Topography regulates the local re-distribution of precipitation, soil moisture, and solar radiation, which in turn affect the distribution of vegetation (Bonan, 2015; Turner et al., 2001). Therefore, four factors, including soil type, DEM (as a combination of topographical factors such as elevation and slope), temperature and precipitation, were selected as the regional environmental influencing factors of NDVI pattern. Previous studies have found that climate change was the main driving factor for NDVI changes, although human activities also had important effects on NDVI changes, but it was weaker than that of these climate factors (Pei et al., 2019; Yang and Han, 2019; Tao et al., 2020; Zhang et al., 2020). Therefore, temperature, precipitation, and three human activity factors including population density, GDP, and land use type (Table 1) were selected to reveal the driving factors of NDVI change in the Qinling-Daba Mountains based on the above mentioned data every five years. As the input data of the Geodetector requires classified data, all the selected factors were classified into the classified data with 9 categories by the natural breakpoint method.

The Geodetector method was constructed on the assumption that when an independent variable has an important effect on a dependent variable, the spatial distribution of the independent variable and the dependent variable should be similar (Wang and Hu, 2012; Wang et al., 2010; Wang and Xu, 2017). It can quantitatively express the spatial stratification heterogeneity of the research object by analyzing the similarities and differences between the intra-layer variance and the inter-layer variance (Hu et al., 2011; Wang et al., 2013). At present, it has been widely used to detect the driving factors in many studies, such as land use (Hu et al., 2011), public health (Wang et al., 2013), regional economy (Ding et al., 2014), regional planning (Liu and Yang, 2012; Yang et al., 2016), meteorology and environment (Du et al., 2016), and vegetation change (Peng et al., 2019; Wang J. et al., 2019; Wang W. et al., 2019). Therefore, this study used the Geodetector method to detect the influencing factors of vegetation pattern and change. The Q-statistic in Geodetector can be used to measure spatial stratified heterogeneity, detect explanatory factors, and analyze the interactive relationship between variables (Wang and Xu, 2017). The range of the Q-statistic is [0, 1], and a larger value of the Q-statistic indicates that the independent variable has the stronger explanatory power on the dependent variable (Wang and Xu, 2017). At the extremes, a Q-statistic value of 1 indicates that the independent variable (X) completely controls the spatial distribution of the dependent variable (Y), and a Q-statistic value of 0 indicates that the independent variable of X has no relationship with the dependent variable of Y. The P-statistic, which corresponds to the Q-statistic of the independent variable (X), can be used to represent the significance of the variable X on the dependent variable Y. For example, a P-statistic of less than 0.05 means that the effect of the variable X on the dependent variable Y is significant, and a P-statistic of less than 0.01 means that the effect of the variable X on the dependent variable Y is highly significant, which can be interpreted as the smaller the P-statistic, the greater the reliability of the inference that a certain type of independent variable X has an effect on the dependent variable Y.

TABLE 1 Environmental influencing factors for NDVI pattern and change in the Qinling-Daba Mountains.

Factors	Code	Indictor	Unit	Factor type*
Geomorphology	X1	Topography	–	①
Soil	X2	Soil type	–	①
Climate	X3	Annual average temperature	°C	①, ②
	X4	Annual precipitation	mm	①, ②
Economy	X5	Population density	Person/km^2	②
	X6	GDP	Ten thousand Yuan/km^2	②
Land use	X7	Land use type		②

*① Controlling factor for NDVI pattern; ② Driving factor for NDVI change.

3 Results

3.1 NDVI spatial patterns and changes in the Qinling-Daba Mountains

3.1.1 The spatial patterns of NDVI

According to the spatial distribution of the average NDVI in the Qinling-Daba Mountains from 1986 to 2019 (Figure 3A), the NDVI showed a U-shaped distribution pattern in latitude and an anti-U-shaped pattern in longitude and with increasing altitude (Figures 3C–E). Mountainous areas such as Qinling Mountains and Daba Mountains, especially the nature reserves such as Shennongjia Nature Reserve and Taibai Mountain Nature Reserve, etc., had higher NDVI average value (above 0.8) than other areas (e.g., Hanzhong Basin area). The Hanzhong Basin-Hanshui Valley in the middle of the Qinling-Daba Mountains, the low-altitude areas of the Funiu Mountain, and some areas in Gansu and Sichuan provinces had lower average NDVI values (between 0.4 and 0.6) than these mountainous areas, and the NDVI values around the cities along the Hanjiang River were even lower than 0.3. The NDVI values in the low-altitude areas in the northeast of the study area and the high-altitude areas in the west of the study area were also relatively low. Statistical analysis of NDVI mean values at different altitudes showed that the NDVI first increased and then decreased with increasing altitude: the NDVI mean value at an altitude below 500 m was 0.6857, at altitudes between 1,000 m and1500 m was 0.7884, and slightly decreased (from 0.7743 to 0.7343) at altitudes between 1,500 m and 3,500 m; above 3,500 m, the NDVI mean value decreased significantly; above 4,000 m, the NDVI mean value decreased to 0.4429 (Figure 3E). The spatial pattern of NDVI in the Qinling-Daba Mountains showed that the physical topography, such as elevation, played an important role in the NDVI pattern.

3.1.2 The temporal changes of NDVI

From 1986 to 2019, the NDVI in the Qinling-Daba Mountains showed a significant upward trend, with an average increase rate of 0.28%/a (R^2 of 0.943) (Figures 3B,G,H), indicating the continuous improvement of the vegetation cover in the study area, which was also found in the previous studies (Liu et al., 2015; Yao and Cui, 2022; Chen et al., 2019a,b). Another characteristic of the NDVI change was that the upward trend of NDVI was more obvious in the low-altitude areas (below 1,500 m), while the high-altitude mountainous areas (above 2000–3,000 m), especially the nature reserves, tended to remain stable, which was also found in our previous study (Yao and Cui, 2022). For example, the places of Longnan County-Tianshui County in Gansu Province, the western part of Funiu Mountain, and the water conservancy area of the South to North Water Transfer Project had higher increasing rates of NDVI value, although where the NDVI values were slightly lower. On the contrary, the western mountainous areas of the study area and the nature reserves (such as the Taibai

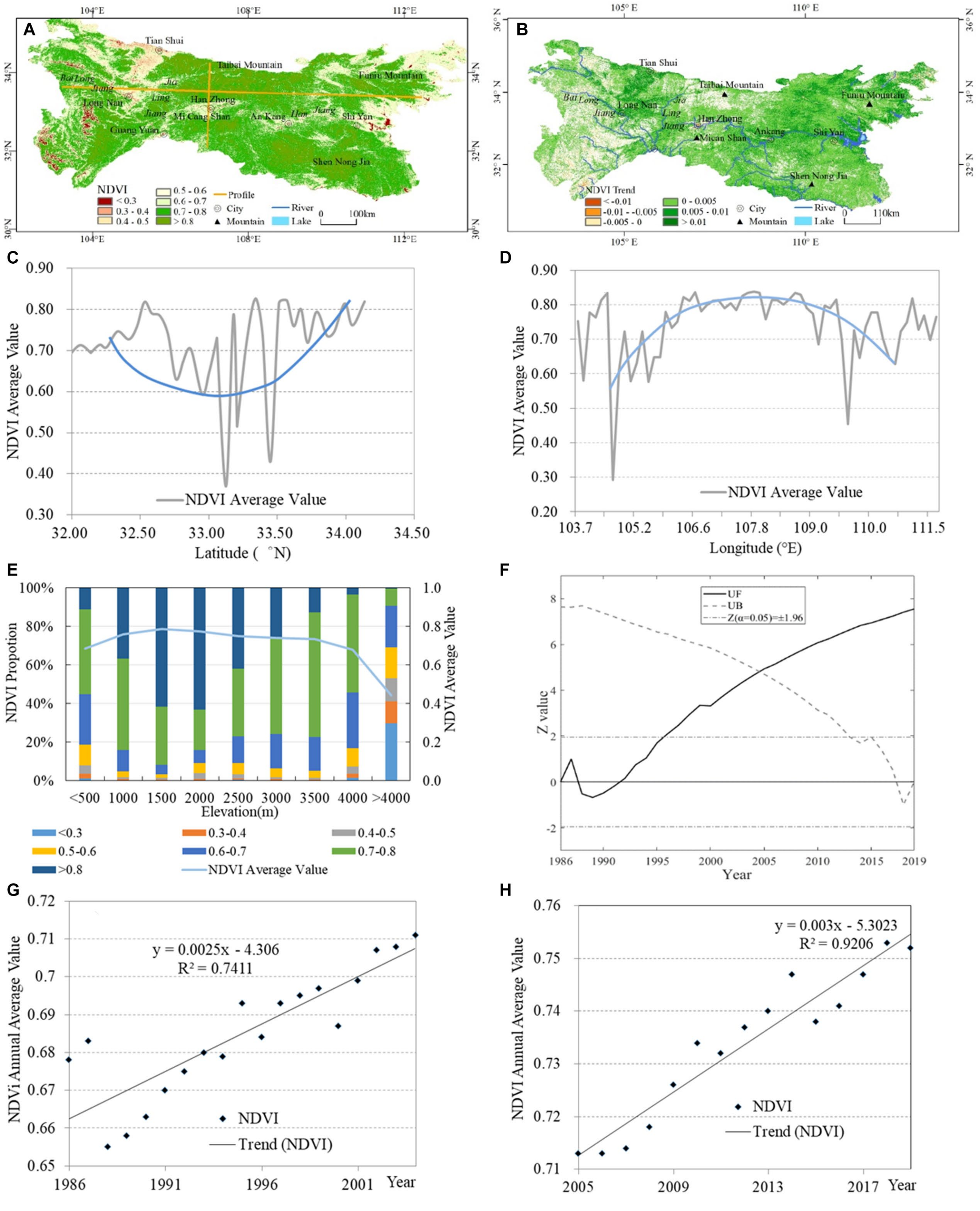

FIGURE 3
The temporal and spatial patterns of the average NDVI in the Qinling-Daba Mountains from 1986 to 2019 [**(A)** Multi-year average NDVI from 1986 to 2019; **(B)** Temporal and spatial variation of NDVI Sen trend from 1986 to 2019; **(C)** Multi-year average NDVI along 107°E profile; **(D)** multi-year average NDVI along 33.6°N profile; **(E)** multi-year average NDVI at elevation; **(F)** MK mutation test of NDVI in the Qinling-Daba Mountains for 1986–2019; **(G)** Annual average NDVI trend from 1986 to 2004; **(H)** Annual average NDVI trend from 2005 to 2019].

Mountain Nature Reserve and Shennongjia Nature Reserve) with high NDVI mean value had lower increasing rates, and the Sen trend values were between-0.005 and 0.005 (which did not pass the significant test at 0.05 level). Of cause, the NDVI value in the surrounding areas of cities and towns showed a decreasing trend (Figure 3B).

The result of MK mutation test on NDVI time series from 1986 to 2019 was the same as that from 1990 to 2019 (Yao and Cui, 2022), which showed that NDVI had a breakthrough increase around 2005 (Figure 3F). Combined with the growth and development characteristics of vegetation, the dynamic process of NDVI in the

Qinling-Daba Mountains could be divided into two periods: the slow increasing period with an increasing rate of 0.25%/a from 1986 to 2004 (R^2 0.74), and the rapid increasing period with an increasing rate of 0.30%/a from 2005 to 2019 (R^2 0.92).

3.2 Environmental influencing factors of NDVI patterns and changes

The Q-statistics of the four factors on vegetation cover pattern were ranked as soil type (X2) > topography (X1) > annual average temperature (X3) > annual precipitation (X4) (Table 2), which showed that physical environmental factors (soil and topography) played stronger influencing roles on the NDVI spatial pattern than climate factors in Qinling-Daba Mountains.

Based on the Geodetector analysis of environmental factors on NDVI change, the explanatory power (Q-statistic) of each factor was ranked as follows: land use type (X7) > annual average temperature (X3) > annual precipitation (X4) > population density (X5) > GDP (X6) (Table 3). This result showed that land use and temperature had stronger effects on regional NDVI changes than precipitation, and the effect of land use was stronger than that of temperature. The effects of population density (X6) and GDP (X7) were relatively weak (Q-statistic less than 0.06).

4 Discussion

4.1 Environmental influences on NDVI spatial pattern at the regional scale

When studying NDVI changes and patterns, climate and anthropogenic factors are often considered, but other environmental factors such as soil and topography are often neglected. It is well known that soil properties such as soil type, texture, pH, and nutrient content have important effects on vegetation growth (Brady and Weil, 2008; Marschner, 2012), and topography redistributes local hydrothermal conditions and soil nutrients, resulting in the changes in temperature, precipitation and vegetation along elevation (Bonan, 2015; Turner et al., 2001; Zhang et al., 2009). In this study, although temperature and precipitation played important roles in the distribution and growth of vegetation, their effects on the spatial pattern of NDVI at the regional scale were weaker than soil and topography. In particular, the effect of precipitation on NDVI pattern was weaker than that of temperature in the study area. Therefore, when studying the influencing factors of NDVI patterns at different scales, we should fully consider the effects of various environmental factors.

4.2 Effects of land use on NDVI changes in the study area

A recent study showed that the "Greening Earth" was attributed to human land use practices in China and India (Chen et al., 2019a,b). This study (Table 3) and other related studies on NDVI change in the Qinling-Daba Mountains also showed that land use had a great influence on NDVI change (Yao and Cui, 2022; Cui et al., 2012; Sun et al., 2010). The Qinling-Daba Mountains is not only an ecological functional area for biodiversity conservation in China, but also a water conservation area for the "South to North Water Transfer Project" in China. Many nature reserves (over 30), national forest parks (about 37), national geological parks (11), and scenic spots (over 7) have been established in the study area from the 1960s to the present. The good condition of the vegetation was one of the achievements of these environmental protections. In addition, the rapid increase of NDVI in the areas below 1,500 m was partly contributed by the land use policies (Chen et al., 2019a,b; Yao and Cui, 2022). The Chinese government issued the Grain-for-Green policy in 1999–2000, and local

TABLE 2 Geodetector analysis results of environmental factors on NDVI pattern in Qinling-Daba Mountains.

	X1	X2	X3	X4
	Topography	Soil type	Annual average temperature	Annual precipitation
Q-statistic	0.289	0.291	0.163	0.098
P-statistic	0.000	0.000	0.000	0.000

TABLE 3 Q-statistics of Geodetector analysis for environmental influencing factors of NDVI change in the Qinling-Daba Mountains.

Year	X3	X4	X5	X6	X7
	Annual average temperature	Annual precipitation	Population density	GDP	Land use type
1990	0.117	0.061	0.039	-	0.167
1995	0.138	0.045	0.052	0.028	0.184
2000	0.132	0.104	0.047	0.030	0.178
2005	0.131	0.107	0.036	0.019	0.185
2010	0.158	0.063	0.045	0.021	0.160
2015	0.175	0.066	0.047	0.026	0.146

P-statistic for every factor was 0.000.

governments formulated strict implementation measures (Chen et al., 2019a,b; Chen et al., 2006; Zhang et al., 2010). One of the achievements of Grain-for-Green was that croplands in mountainous areas with slopes steeper than 25° were required to be returned to forest (or grassland), and those with slopes between 15° and 25° were conditionally returned to forest or grassland (Chen et al., 2006; Zhang et al., 2010). During the field survey of the "Comprehensive Scientific Investigation of the North–South Transitional Zone" project, it was also found that a large number of croplands in the mountainous areas below 1,500 m were returned to forest. Moreover, the croplands also contributed to the increase in NDVI due to the rapid growth of hybrid cultivars, multiple cropping, irrigation, fertilizer use, pest control, improved seed quality, farm mechanization, credit availability, and crop insurance schemes (Chen et al., 2019a,b; Yao and Cui, 2022). Therefore, places below 1,500 m have higher NDVI increases, and the breakthrough increase period was around in 2005 (Figure 3). All these indicate that land use in the Qinling-Daba Mountains has had a positive effect on vegetation dynamics in recent years, and its effect on NDVI change was even stronger than that of climate warming. The temperature of the study area has been warming significantly, while the precipitation has been increasing slightly (Yao and Cui, 2022). That is why the effect of precipitation was weaker than that of land use and temperature on NDVI change in this area.

4.3 Appropriate indicators of anthropogenic factors

Due to the lack of high-resolution quantitative data on human activities (Xie and Yao, 2024), most quantitative analyses of human activities have focused on land use, population density, or GDP. However, except for land use data, the resolution and quality of population density and GDP data are not good enough to characterize human activities. As a result, the results obtained are not satisfactory. Additionally, infrastructure construction such as transportation and roads, social and economic development, and urbanization also affect the NDVI change. Therefore, which indicators can better reflect the impact of human activities on NDVI, especially how to objectively evaluate the impact of human activities on NDVI, remains to be further explored. Moreover, human activities have greatly affected every aspect of the Earth and have a profound influence on vegetation change, so there is a need for a more comprehensive indicator that can synthesize the various human activities. Recently, quantitative methods for assessing and analyzing the impact of human activities on the natural environment, as well as data products, have also developed rapidly. Human activity intensity (HAI) has been widely used to assess and quantify the impacts of human activities on landscapes (Goudie, 2018; Shrestha et al., 2021). There are some useful HAI data products such as HAI data (Xie and Yao, 2024), the global human footprint map (Sanderson et al., 2002; Venter et al., 2016; Mu et al., 2022) and the wildness map (Lin et al., 2016; Cao et al., 2019), which can greatly facilitate our analysis of the impact of human activities on NDVI.

5 Conclusion

The aim of this study is to discover the spatial pattern of NDVI and its environmental influencing factors in Qinling-Daba Mountains, and to find out which factor among of them plays a more important role in the NDVI change in recent decades. The conclusions of this study are as follows:

1. NDVI in the Qinling-Daba Mountains showed a U-shaped pattern in latitude, and anti-U-shaped patterns in longitude and with increasing altitude, indicating that the topography played an important role in the regional NDVI pattern.
2. NDVI in the Qinling-Daba Mountains showed a significant upward trend and experienced a dynamic change process (with a breakthrough increase period around 2005) for 1986–2019. According to the results of this study, the process of vegetation dynamics could be divided into two periods: the slow increase period from 1986 to 2004 (with an increase rate of 0.25%/a) and the rapid increase period from 2005 to 2019 (with an increase rate of 0.30%/a). The rapid increase period was coincided with the implementation period of the Grain-for-Green project and other ecological restoration projects in the early 21st century, which showed that land use, especially those forest conservation and expansion programs, strongly contributed to the NDVI increase.
3. Soil and topography played a more important role in the spatial pattern of NDVI than climate (temperature and precipitation) at the regional scale. The effect of land use on NDVI change was stronger than that of climate warming (temperature), and the climate warming in recent decades played a more important role than precipitation on the NDVI dynamics.

The results of this study indicated that the physical environmental factors such as soil, topography and climate control the spatial pattern of NDVI, and human activities play a more important role in NDVI change than climate change in recent decades. It is useful for the government and other related agencies to formulate plans or policies for infrastructure development and land management, ecological restoration.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found at: the NDVI data for 1986–2019 used in this study are available from the authors upon request; ASTER GDEM can be downloaded from https://earthdata.nasa.gov/; Land cover and land use, soil, geomorphology, temperature and precipitation, vegetation type map, population density and GDP data can be accessed from the Data Center of Resources and Environment Science, Chinese Academy of Sciences (http://www.resdc.cn).

Author contributions

YY: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

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