EXPLORING THE DRIVING MECHANISMS OF REGIONAL VEGETATION COVER CHANGE USING A COMBINATION OF FACTOR REGRESSION AND FACTOR INTERACTION IN THE LIAOHE RIVER BASIN, CHINA

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Abstract. Comprehending the underlying mechanisms governing the dynamics of vegetation alteration constitutes a fundamental prerequisite for the effective implementation of ecological construction. In this study, the spatial heterogeneity of vegetation coverage in the Liaohe River Basin (LHRB) in China from 2000 to 2019 was analyzed using the Normalized Difference Vegetation Index (NDVI) derived from MOD13Q1 product. It proposed to combine factor regression and factor interaction to jointly explore the effects of factors on the NDVI. The results showed that: (1) The NDVI in the LHRB showed an overall increasing trend from 2000 to 2019; (2) Precipitation emerged as the predominant factor exerting influence on vegetation change across the basin, and the change trend of NDVI was synchronized with precipitation; (3) The interactions between two environmental factors had a greater influence on NDVI than any single factor. The interactions of natural factors played a dominant role; (4) The gradient changes in precipitation affected the explanatory power of other factors for NDVI. With the increase of precipitation, the activity of other factors kept getting stronger, and the fit of other factors to NDVI improved; (5) The human activities have generally been dominated by positive effects in the LHRB over the past 20 years.
Keywords: *vegetation change, normalized difference vegetation index, driving factors, Bayesian regression, geo-detector, Mann-Kendall test, Liaohe river basin (LHRB)*

Introduction

Vegetation, playing a crucial role in the terrestrial ecosystem, serves as both the producer of organic matter and the conduit for energy transfer. Additionally, it acts as a vital link connecting the atmosphere, soil, and water (Ding et al., 2020). Vegetation change is a sensitive indicator of environmental change, which can directly reflect the overall condition of the ecological environment (Wen et al., 2017), and then provides reliable information for ecological construction and protection (Zhong et al., 2019). Hence, closely monitoring vegetation changes and investigating the underlying drivers can enhance our comprehension of the intricate interactions between vegetation and ecology. This, in turn, can offer valuable insights and guidance for the preservation and conservation of terrestrial ecosystems.

In recent years, with the launch of various earth observation satellites and the rapid development of photogrammetry, ecological environment monitoring based on remote-sensing technology has become indispensable (Pettorelli et al., 2014; Zhu et al., 2016; Gao et al., 2020). Out of the various vegetation indices derived from remote sensing data, the Normalized Difference Vegetation Index (NDVI) has been extensively employed to track fluctuations in vegetation dynamics attributed to its straightforward inversion

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algorithm and clear physical interpretation (Verbesselt et al., 2010; Fensholt and Proud; 2012). Several researchers have made fruitful studies on global and regional vegetation change based on NDVI datasets (Fan and Liu, 2016; Liao et al., 2016). At the global level, global vegetation cover has increased since 1980, which may be mainly due to improved climatic conditions and increased carbon dioxide concentrations (Wu et al., 2014). However, some scholars have pointed out that since 2000, with the continuous warming climate, the global vegetation faced the risk from long-term increase to degradation (Li and Yang, 2014; Yu et al., 2020). At the regional scale, the change trends of NDVI were different, had spatial heterogeneity, and were associated with a variety of influencing factors (Schulz et al., 2011; Liu et al., 2018). Therefore, understanding the diversity and interactions of the driving factors of NDVI change is the key to studying the vegetation change mechanisms.

Studies have examined and summarized the environmental factors influencing vegetation change, which mainly involved natural and anthropogenic factors, such as precipitation (Gao et al., 2020), temperature (Wang et al., 2021), elevation (Herrmann et al., 2016), population density (Zhang et al., 2022). Due to differences in external environmental factors, there is substantial variability in vegetation changes and the factors that influence them at regional scales, and the responses of NDVI to environmental factors are also different in different regions, implying that the drivers of NDVI are spatially heterogeneous. For example, the characteristics and drivers of NDVI change in arid and semi-arid areas differed greatly from those in humid and semi-humid areas (Zhan et al., 2022). There were also great differences in NDVI distribution characteristics and influencing factors among different geographic areas (such as mountains, plains and deserts) (Liu et al., 2018). Hence, it is imperative to investigate the spatial distribution patterns and underlying drivers of NDVI at the regional scale to facilitate the implementation of localized measures for vegetation restoration and ecological conservation.

Currently, the predominant approach employed by scholars involves the utilization of linear analysis, trend analysis, and correlation analysis to qualitatively assess the spatial and temporal variations in vegetation cover. Furthermore, most studies investigating vegetation change and its driving mechanisms assume a substantial linear association between the driving forces and vegetation across the entire time series (Palmate et al., 2017; Lamchin et al., 2020). However, the response of vegetation to the external environment is a very complex process, and absolute statistical linear relationships rarely exist in natural environments. This implies that the analysis of drivers on vegetation change based on linear assumptions may have some bias. In addition, previous studies have predominantly treated natural and anthropogenic factors as independent variables, disregarding their interactive effects on vegetation change.

In contrast to conventional regression analysis, the Geo-detector presents a novel statistical approach for identifying spatial heterogeneity in geographic phenomena and investigating their underlying driving mechanisms (Wang and Xu, 2017). The fundamental principle of the Geo-detector lies in the observation that if an independent variable exerts a notable influence on a dependent variable, their spatial distributions should exhibit similarities (Wang et al., 2016). An important strength of this approach is its capability to detect the interaction between two influencing factors without following the linear hypothesis (Song et al., 2020). The method has been successfully applied in many fields in recent years, including vegetation changes (Palmate et al., 2017), surface subsidence (Ding et al., 2021), soil degradation (Zhao et al., 2021) and environmental

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pollution (Guo et al., 2022). The Geo-detector, while capable of effectively detecting the effect of factor interaction on geographical phenomena, also has some shortcomings. Firstly, it is unable to determine the positive or negative correlation of the effects of independent factors on geographical phenomena, and secondly, it lacks the capability of a regression model to accurately simulate the characteristics of the dependent variable. At present, there are few studies on combining factor regression and factor interaction to explore the driving factors affecting vegetation change. Hence, this study employed the MODIS NDVI data, along with the Sen+MK test, Bayesian linear regression, and the Geo-detector model, to quantitatively examine the characteristics of vegetation change and its driving mechanisms in the LHRB from 2000 to 2019. This approach aims to offer a scientific foundation for the sustainable development of the local ecological environment.

Materials and methods

The case study

The Liao River, one of China's seven major rivers, has its source in the Guangtou Mountains located in Hebei Province. It traverses through the provinces of Hebei, Jilin, Inner Mongolia, and Liaoning before eventually emptying into the Bohai Sea. Spanning a total length of 1,345 kilometers. Its main tributaries include the Hun River, Prince River, Daliao River, Xiliao River and Dongliao River. The Liaohe River Basin spans the arid, semi-arid and humid areas of China, with a total area of 219,000 square kilometers. The unique geographical location also creates complex climate types and fragile ecological environment in the region. The area is a typical transition zone between monsoon and continental climates and is also a crossroads of agricultural and pastoral activities in China. The whole basin can be divided into the eastern agricultural plain dominated by agricultural activities, the central and western pastoral grasslands and deserts dominated by animal husbandry activities, and the Agro-Pastoral area between them (*Figure 1c*). Within this diverse climatic region, the LHRB also displays significant variations in the duration of frost-free periods and the vegetative growth periods of major crops. The agricultural plains in the eastern part of the basin generally experience extended frost-free periods, which are conducive to the growth of key crops such as wheat and maize, as well as prolonged vegetation growth periods. In contrast, the pastoral grasslands and desert areas in the west-central part of the basin encounter shorter frost-free periods, posing challenges for the growth of grasses and forage crops, along with more limited vegetation growth periods. This diversity in climatic and vegetation conditions profoundly impacts the development of agriculture and animal husbandry, as well as the preservation of ecological balance in the region. With the climate change and increasing human activities, the vegetation condition of the LHRB has been changing. Therefore, understanding the vegetation change characteristics in a watershed and their underlying driving forces is a prerequisite for developing effective vegetation conservation policies.

Data sources and processing

The vegetation data was sourced from the MOD13Q1 NDVI product, and it download from the National Aeronautics and Administration, and the Maximum Value Composite method was used to obtain the annual NDVI from 2000 to 2019. Population, nighttime lights and Gross Domestic Product (GDP) data in the study area from 2000-2019 were

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downloaded from the Center for Resources and Environment of the Chinese Academy of Sciences (https://www.resdc.cn/). Temperature, precipitation, and wind speed data came from the National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn), with a 1km resolution. Digital Elevation Model data came from the Geospatial Data Cloud (http://www.gscloud.cn/) with a spatial resolution of 90m, the slope was calculated by DEM data in the ArcGIS tool. Solar radiation data were obtained from the National Meteorological Science Data Center (http://www.data.cma.cn/). 27 monitoring stations in the basin were selected and interpolated using the Kriging tool in the ArcGIS tool to obtain the solar radiation data for the study area. Data on rivers, main roads and settlements also came from the CRECAS (https://www.resdc.cn/), and the distances to rivers, main roads, and settlements were calculated by the spatial analysis tool in ArcGIS. 2263 regular grid sizes of 10km×10km were created in the basin, and the values of NDVI and 12 factors were extracted for each grid. Because Geo-detector is better at dealing with discrete variables, the Natural Breakpoint Method was used to convert the 12 continuous variables into discrete variables (Hong et al., 2018). To simultaneously balance the vegetation growth continuity and reduce the complicacy of data visualization, when exploring the driving factors of vegetation, we selected five node years, namely 2000, 2005, 2010, 2015 and 2019, for data mapping and analysis.

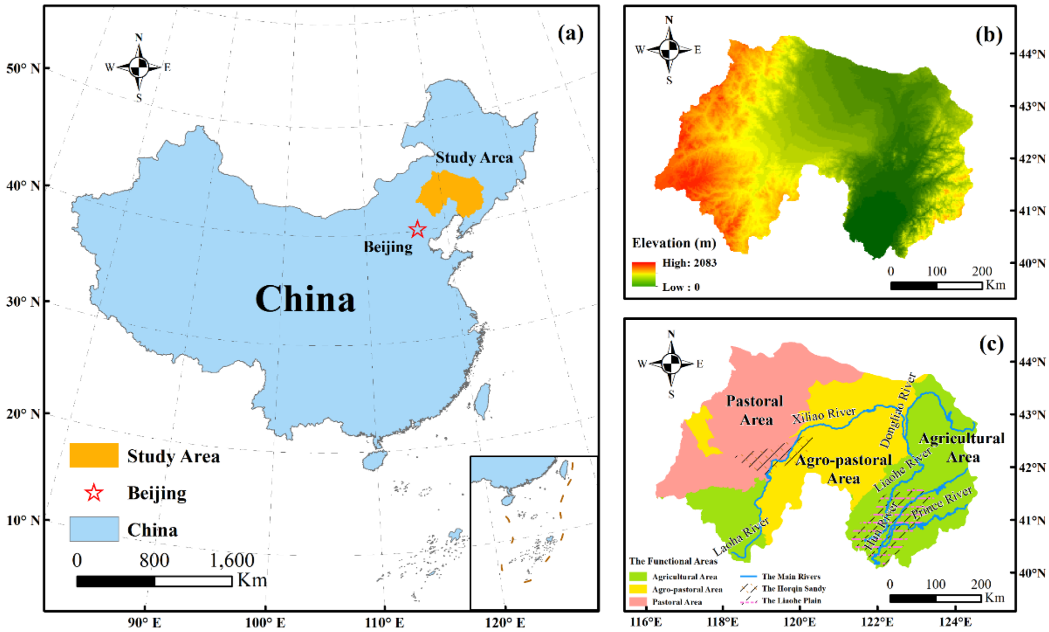

Figure 1. *(a) Location of the LHRB; (b) The elevation of the basin; (c) The functional areas of basin*

Methods

The framework of the research is shown in *Figure 2*. First, the Sen+ Mann-Kendall test were used to analyze the spatial-temporal distribution and change characteristics of NDVI. Then, the Bayesian linear regression and Geo-detector were used to jointly explore the drivers on NDVI.

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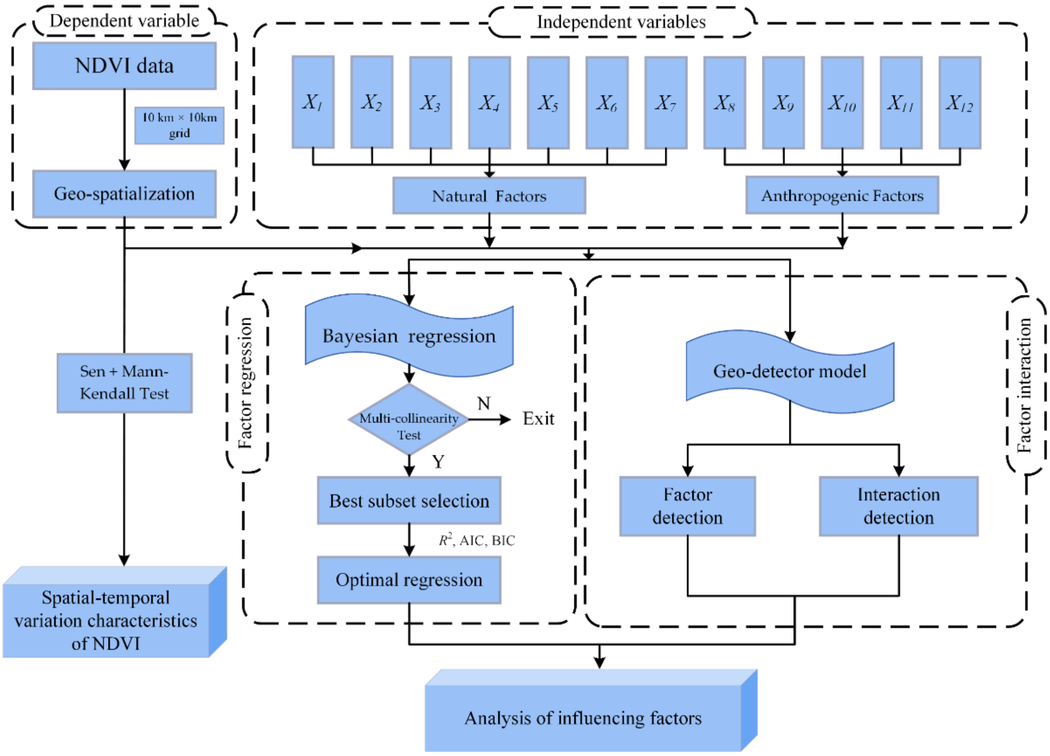

***Figure 2.** Research framework. (In this figure, the X_1-X_{12} variables are respectively represented Elevation, Slope, precipitation, temperature, solar radiation, wind speed, Distance to the rivers, Population density, Nighttime light intensity, Distance to the settlements, GDP, Distance to the roads)*

NDVI trend analysis

The Sen and Mann-Kendall trend test were used to investigate the vegetation trends in the LHRB over the past 20 years. Compared with the ordinary least squares trend analysis, Sen's slope analysis offers several advantages in terms of reducing the influence of outliers and enhancing the accuracy of test results.

$$\theta_{\mathrm{slope}} = \mathrm{Median}\left(\frac{x_j - x_i}{j - i}\right), \qquad \forall\, j > i \tag{Eq.1}$$

where θ_{Slope} is the vegetation change trend, Median is the median function, and x_i, x_j are the NDVI data of the i and j years. When $\theta_{Slope} > 0$, NDVI shows a rising trend, and vice versa, a downward trend. To better study the vegetation change, the NDVI was divided into five classes (Liu et al. 2021), as shown in *Table 1*.

***Table 1.** The NDVI Classifications*

Class	Level	NDVI
1	Bare land vegetation	0-0.2
2	Low vegetation	0.2-0.4
3	Medium vegetation	0.4-0.6
4	Medium-high vegetation	0.6-0.8
5	High vegetation	0.8-1.0

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Then, the Mann-Kendall test was performed on NDVI data from 2000-2019. The correlation equations are as follows:

$$S = \sum_{t}^{t-1} i \sum_{j=i+1}^{t} \mathrm{sign}(\mathrm{NDVI_i} - \mathrm{NDVI_j}) \quad \text{(Eq.2)}$$

$$\mathrm{sign}(\mathrm{NDVI_i} - \mathrm{NDVI_j}) = \begin{cases} -1, \mathrm{if}(\mathrm{NDVI_i} - \mathrm{NDVI_j}) < 0 \\ 0, \mathrm{if}(\mathrm{NDVI_i} - \mathrm{NDVI_j}) = 0 \\ 1, \quad \mathrm{if}(\mathrm{NDVI_i} - \mathrm{NDVI_j}) > 0 \end{cases} \quad \text{(Eq.3)}$$

the variance of S is computed by:

$$\mathrm{Var}(S) = \frac{t(t-1)(2t+5)}{18} \quad \text{(Eq.4)}$$

the statistics Z is defined as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\mathrm{Var}(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{\mathrm{Var}(S)}} & S < 0 \end{cases} \quad \text{(Eq.5)}$$

where, *S* obeys normal distribution, $NDVI_i$, $NDVI_j$ are the starting and ending time series of NDVI to be tested, and *sign* is the sign function. According to the normal distribution table, the critical value $Z_{1-\alpha/2}$ is obtained at a significance level α, when $|Z| \leq Z_{1-\alpha/2}$, the trend change is not significant; when $|Z| > Z_{1-\alpha/2}$, the trend change is considered significant. In this study, the significance level was set at 0.05 and the critical value $Z_{1-\alpha/2}$ was 1.96 (Tian et al., 2017).

Factor selection

Both natural and socio-economic factors have important contributions to vegetation change. Considering that seasonal variations may not be sufficient to fully reflect the ecosystem function of vegetation, and in order to better study the multi-year long-term trend of vegetation change, we chose the NDVI of the region for the whole year as the dependent variable in this study. At the same time, we selected 12 representative, easily accessible and quantifiable factors from climate, topography, geomorphology, rivers, and human activities as independent variables (*Figure 3* and *Table 2*). The yearly sum of precipitation and yearly average temperature have been identified as the two primary driving factors significantly impacting vegetation change. Other natural factors such as altitude, slope, yearly average wind speed and total solar radiation (Schulz et al., 2011; Herrmann et al., 2016; Zhang et al., 2022) can influence the evapotranspiration and water utilization of vegetation, which in turn affect vegetation growth. In addition to precipitation, the rivers are an important source of water recharge for vegetation in arid zones (Shen et al., 2017), so we used the distance to the rivers as an independent variable. Empirical studies have proven that population, nighttime lighting, distance to the roads,

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distance to the settlements, and GDP can availably reflect the human activity intensity (Zheng et al., 2019; Ma et al., 2021), so those five factors were included as independent variables too.

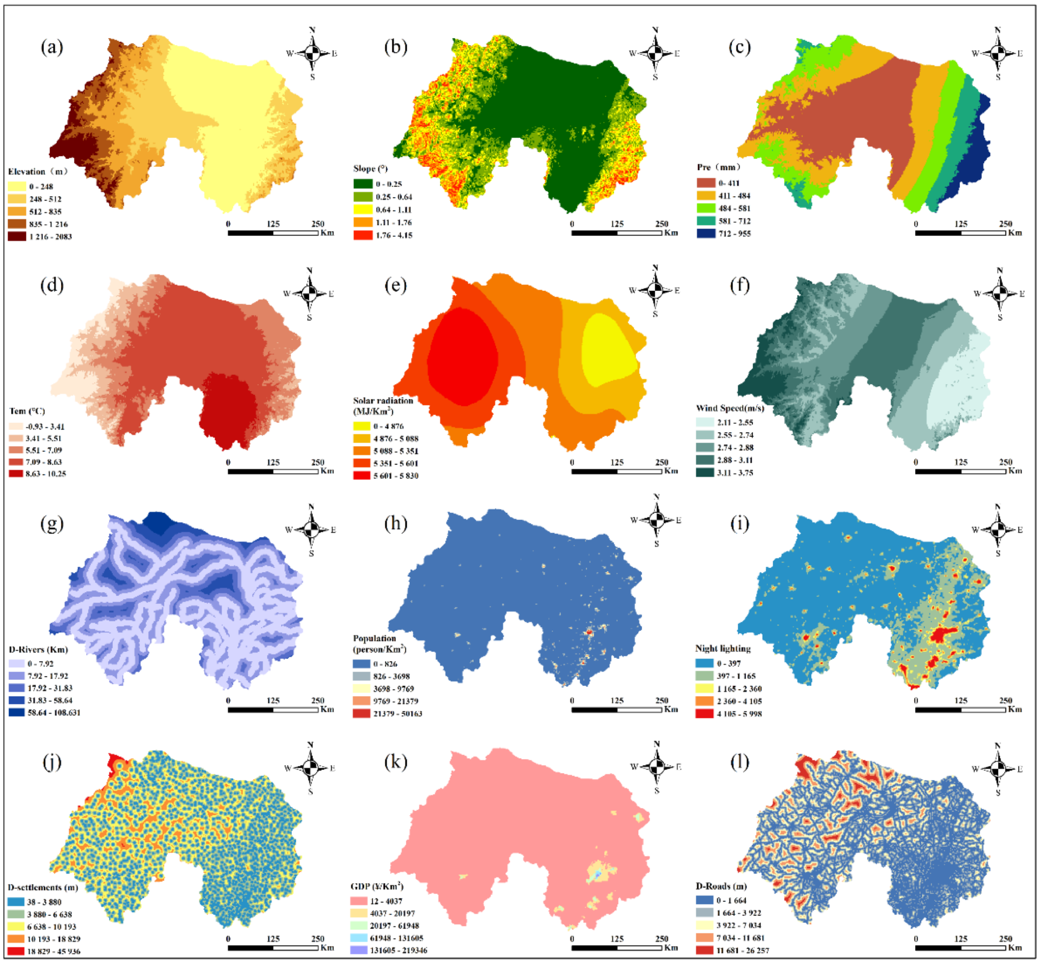

Figure 3. *Spatial distribution of influencing factors in Laiohe River Basin*

Table 2. *The influencing factors on NDVI*

Respects	Variables	Code	Unit
Vegetation	NDVI	Y	-
Topography	Elevation	X_1	m
	Slope	X_2	degree
Climate	precipitation	X_3	mm
	temperature	X_4	°C
	solar radiation	X_5	MJ/m^2
	wind speed	X_6	m/s
River	Distance to the rivers	X_7	km
Human activity	Population density	X_8	$Person/km^2$
	Nighttime light intensity	X_9	gray
	Distance to the settlements	X_{10}	km
	GDP	X_{11}	¥/km^2
	Distance to the roads	X_{12}	km

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Bayesian linear regression

The Bayesian algorithm is an efficient, classical and simple tool, which has been widely used in many fields (MacNab, 2014). It can effectively avoid the phenomenon of over-fitting by introducing a Gaussian prior to achieving penalized parameters for variables (van Erp et al., 2019). For the random vector a (parameter) and b (samples data), the Bayesian formulation is as follows:

$$\mathrm{P(a|b)} = \frac{\mathrm{P(b|a)P(a)}}{\mathrm{P(b)}} \tag{Eq.6}$$

where $P(a|b)$ is the posterior distribution for the parameter; $P(a)$ is the prior distribution. $P(b)$ is the marginal distribution density of b, and $P(b|a)$ is the density function of b given the parameter a.

Bayesian linear regression is a linear regression tool based on Bayesian algorithm (Klauenberg et al. 2015). Define the sample data $X_i(\text{independent variable}) = \{X_{1,}X_{2,}\ldots. X_n\}$, $Y_i(\text{dependent variable,}) = \{Y_{1,}Y_{2,}\ldots. Y_n\}$, *m* is the sample size, the BLR can be obtained as follows:

$$\mathrm{f(X_i) = X_i{}^T w} \tag{Eq.7}$$

$$\mathrm{Y = f(X_i) + \varepsilon} \tag{Eq.8}$$

where: ε is the residual, *w* is the weight coefficient.

Best subset selection

Best subset selection is a method that considers all possible combinations of independent variables in order to identify the optimal combination that yields the best predictive performance for the dependent variable (Di Gangi et al., 2019). The main calculation procedure is as follows. ① Based on the principle of "maximum adjusted R^2 (R^2_{adj}) ", the dependent variable is fitted with n predictor variables and suitable combinations of independent variables are selected from the n predictor variables. ② Calculate the R^2, Akaike information criterion (AIC) and Bayesian information criterion (BIC) of the above combinations in turn. The R^2 is used to comprehensively judge the fit to Y. The larger the R^2, the higher the accuracy of the fit. The AIC and BIC are used to determine whether the model is overfitting. Smaller values of AIC and BIC can reduce the overfitting degree of model (Aho et al., 2014). Finally, the best subset of independent variables is selected by considering the value of R^2, AIC and BIC together.

Geo-detector

The Geo-detector is new an open-source model used for spatial statistical analysis (http://www.geodetector.cn/) (Wang and Xu, 2017). Its functions include factor detector, interaction detector, ecological detector and risk detector, and we used the first two functions in this study.

The factor detector is used to detect the explanation degree of each influence factor on NDVI(*Y*) by the PD value:

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$$PD = 1 - \frac{1}{N\sigma^2}\sum_{h=1}^{L} N_h \sigma_h^2 \tag{Eq.9}$$

where, h=1,2, ... p. L is the layer of the factor (X) or variable (Y); N and N_h are the number of units in layer h and the whole region respectively; σ_h^2 and σ^2 are the variances of the (Y) value, respectively. The PD takes values in the range [0,1]. The larger the value of PD, the stronger the explanatory power of the factor(X) to the variable (Y), and PD = 0 means that the two are unrelated.

The interaction detector was used to explore whether there is an interaction between the two drivers and the extent to which this interaction explains Y(NDVI). The method of evaluation is first to calculate separately the PD values of factor X_1 and factor X_2 on Y, then calculate the PD values when they interact, and finally compare the magnitude of PD values among the three.

Results

Vegetation pattern during the 2000–2019 period

Spatial distribution of the NDVI

The average NDVI for the period of 2000 to 2019 was computed at the raster scale. Subsequently, the proportion of different NDVI classes within the total area of the corresponding sub-region was determined (*Figure 4*). The findings revealed a spatial pattern of higher NDVI values in the eastern region and lower values in the western region of the study area. The average NDVI value for the entire basin during the 20-year period was 0.69, indicating a generally high level of vegetation cover. The proportions of bare land vegetation, low vegetation, medium vegetation, medium-high vegetation, and high vegetation were 0.34%, 14.77%, 23.53%, 25.35%, and 35.51% of the total basin area, respectively.

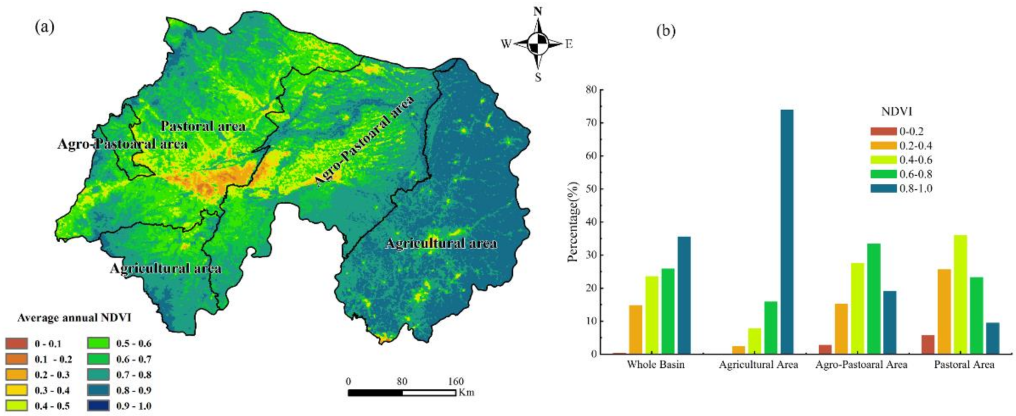

Figure 4. *(a) Spatial distribution of average annual NDVI from 2000 to 2019; (b) The proportion of different classes of NDVI in each functional area*

On the one hand, bare soil and low vegetation cover areas were primarily distributed in the central and northern pastoral area and Agro-Pastoral area, including Wengniut Banner, Bahrain Right Banner, central and western Naiman Banner, northern Kulun

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Banner, etc. The climate was dry and cold, precipitation was scarce, and vegetation was sporadically distributed in those areas. On the other hand, the medium-high vegetation and high vegetation cover were primarily distributed in the agricultural area in the eastern part of the basin, most typically in the Liaohe Plain, where the growing vegetation was dominated by cultivated crops. With flat terrain, more rainfall, well-developed irrigation system and luxuriant vegetation, this area is an important commercial grain production base in China. In addition, there were also some NDVI low-value centers in the eastern plains of the study area, and most of which were located around cities. This might be due to the urban expansion and human activities that occupied a large amount of agricultural and ecological land, resulting in the decrease of NDVI (Yang et al., 2021). Meanwhile, it can be seen from *Figure 4* that the vegetation cover in the study area had obvious spatial heterogeneity, ranked in descending order of mean NDVI as: Agricultural area> Agro-Pastoral area > Pastoral area.

Temporal and spatial changes in NDVI

Figure 5a showed the characteristics of the distribution of NDVI from 2000 to 2019, from which we could see that the average value of NDVI showed a fluctuating upward trend. Moreover, the positions of the upper and lower quartiles indicated that the proportion of high vegetation cover was much larger than that of low vegetation cover in the past 20 years, and the overall level of NDVI in the basin was high. In order to better analyze the trend of vegetation over 20 years, a linear regression equation of vegetation versus year was established. *Figure 5b* showed that: (1). The NDVI of the entire basin has been on an upward trend for 20 years, and the slope of the linear regression trend line was 0.0044, indicating a slow overall increasing trend. (2). For the rising trend of vegetation in each functional area within the basin, Agro-Pastoral area > Pastoral area > Agricultural area. (3). The fluctuation of vegetation in the agricultural area was the smallest in the past 20 years, while that in the pastoral area was the largest, which may have something to do with human activities. Previous studies have also confirmed this view (Chen et al., 2021).

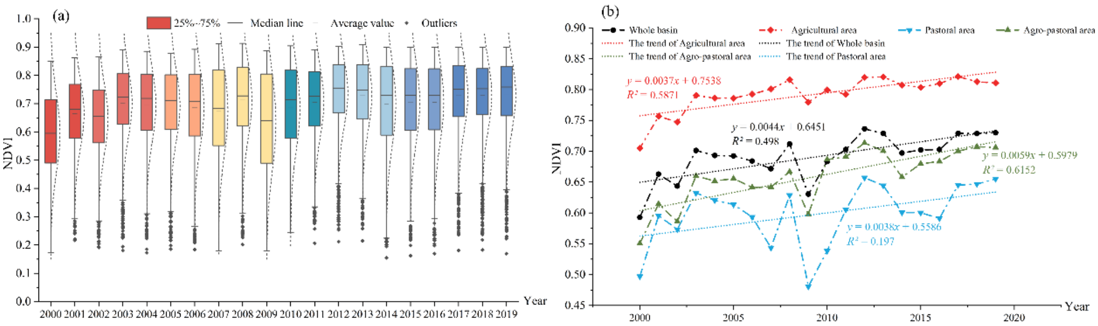

Figure 5. *(a) The distribution characteristics of NDV from 2000 to 2019; (b)The change trend of NDVI from 2000 to 2019*

The change in the annual mean NDVI time series reflected the general trend of vegetation change but could not reflect the spatial variation of vegetation and the significant difference of change. Hence, the Mann-Kendall trend test was employed to assess the statistical significance of the spatial variability in vegetation. *Figure 6* illustrated that the regions exhibiting a notable increase in NDVI were primarily

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concentrated in the eastern and northern parts of the agricultural region, along with the southern low mountainous and hilly areas within the study area. The areas with the significant decrease of NDVI were mainly concentrated in the grasslands and deserts in the pastoral area, where the problems of salinization and desertification were serious, resulting in vegetation degradation. There were also some significantly decreased areas in the eastern part of the basin, which were sparsely distributed around the cities. This might be related to the fact that urban land expansion occupied a large amount of ecological land and farmland, resulting in significant vegetation degradation. This observation is in line with previous research findings as well (Yang et al., 2021).

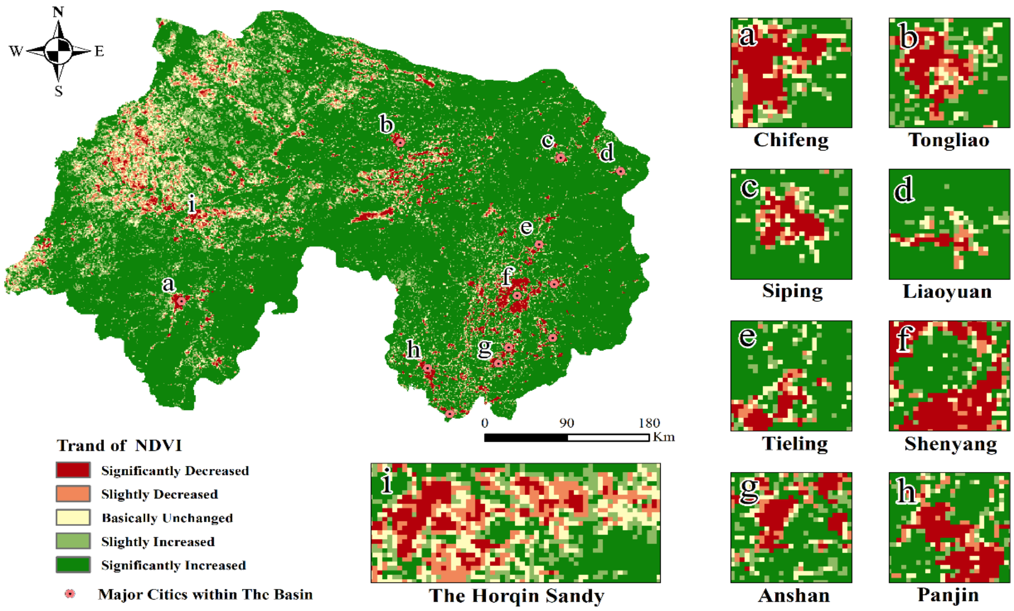

Figure 6. *The spatial change of NDVI from 2000 to 2019*

In the past 20 years, high cover vegetation (0.8-1) was the main interval of vegetation cover change (*Figure 7*). The significant increase in vegetation was primarily observed in the eastern plain area of the basin, characterized by black soil, known for its high organic matter content. The main type of vegetation is cash crops, and the community structure is simple, which is greatly affected by human activities. In recent years, the local government has implemented stronger measures to protect agricultural and forestry land, such as designating the red line for arable land protection and prohibiting the illegal occupation of arable land and forest land, etc. As a result of these measures, there has been a significant increase in the vegetation cover of the area. In addition, we also found that the range of vegetation change gradually decreased, and the coverage area of each grade tended to be stable.

Bayesian linear regression analysis

Multi - collinearity test

It is essential to conduct tests for multicollinearity among the independent variables as strong correlations between variables can distort the model estimation (Gholami et al., 2021). *Table 3* demonstrated that all independent variables exhibit a variance inflation

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factor (VIF) of less than 10 and a tolerance (1/VIF) greater than 0.1. These results align with the assumption of independence required by the regression model. (Gholami et al., 2021).

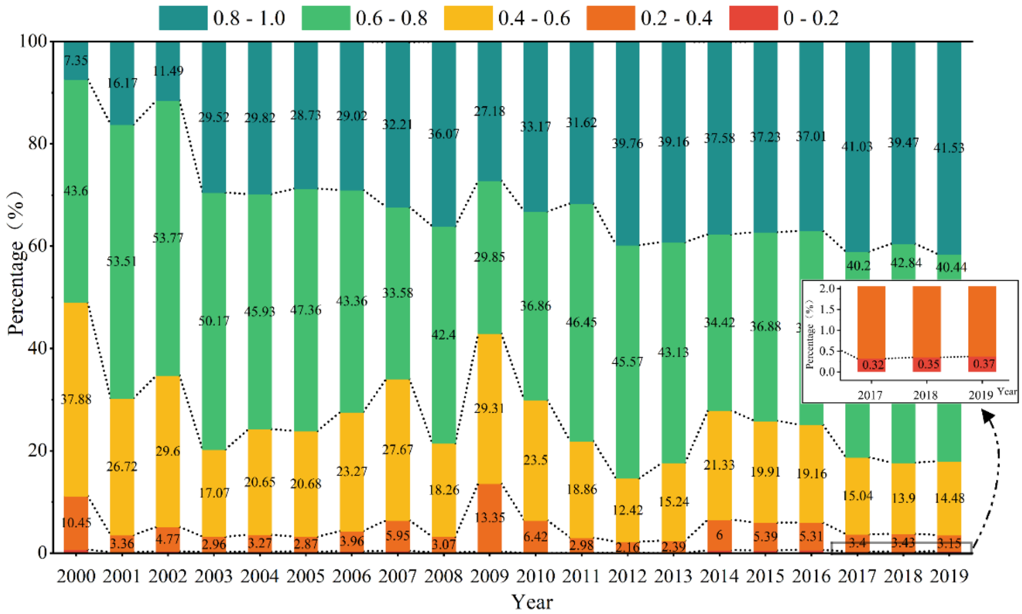

***Figure 7.** Area percentage of NDVI classification from 2000 to 2019*

***Table 3.** The VIF values of all independent variables*

A / Y	Whole basin		Agricultural area		Agro-Pastoral area		Pastoral area	
	$\overline{VIF}$	$\overline{1/VIF}$	$\overline{VIF}$	$\overline{1/VIF}$	$\overline{VIF}$	$\overline{1/VIF}$	$\overline{VIF}$	$\overline{1/VIF}$
2000	3.722	0.269	3.836	0.261	2.769	0.361	5.741	0.174
2005	3.852	0.260	3.238	0.309	3.359	0.298	4.103	0.244
2010	4.259	0.235	3.892	0.257	3.582	0.279	4.659	0.215
2015	2.968	0.337	3.568	0.280	5.962	0.168	4.368	0.229
2019	5.364	0.186	3.259	0.307	3.569	0.280	4.128	0.242

Note: The A denotes Areas; the Y denotes Years; $\overline{VIF}$ denotes the mean VIF of all independent variables; $\overline{1/VIF}$ denotes the mean 1/VIF of all independent variables

Regression models with the optimal combination of influencing factors

The 12 factors were standardized, and the variable combinations was determined by adjusting R^2 (R^2_{adj}), and then the optimal subset of models was selected. For each subset of models, the fitting degree of the model to the variable NDVI(Y) was evaluated by R^2. A higher value of R^2 indicates a better fit of the model. The AIC and BIC are used to detect whether the model is overfitted. Their smaller values can reduce the overfitting of models.

Table 4 listed the optimal combination equations obtained based on the best subset selection and the three independent variables with the largest regression coefficients in the equation. The results showed that except for the Agro-Pastoral area in 2010, the variable with the largest absolute coefficient in the regression function of all years and regions was X_3 (precipitation). It could be explained that the effect of precipitation on

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NDVI was particularly significant in most years from 2000 to 2019. Therefore, this paper focused on the relationship between annual precipitation and vegetation change, and *Figure 8* showed the trends of precipitation and NDVI of each functional area over 20 years. It can be seen from *Figure 8* that both in the agricultural and pastoral areas, the changes in NDVI were synchronized with the changes in precipitation. The increased values of NDVI in the years when precipitation increased, indicating that precipitation significantly influenced vegetation change and was an important factor affecting vegetation growth. It can be seen that there is a certain positive correlation between precipitation and NDVI.

Table 4. *Optimal regression equations for different regions and years*

Year	Areas	Regression model equations	R^2	Ranking size
2000	Whole basin	0.064-0.301X1+0.166X2+0.700X3-0.188 X4+ 0.208X6+0.184X8-0.064X9-0.046X10-0.057X11	0.703	X3>X1>X6
	Agricultural area	0.049-0.174X2+0.822X3-0.046X5+0.256X6- 0.077X7+0.077X8-0.331X9-0.068X10	0.723	X3>X9>X6
	Agro-pastoral area	0.085-0.468X2+0.770X3-0.297X4-0.261X6+ 0.233X8+0.220X11-0.066X12	0.574	X3>X2>X6
	Pastoral area	0.262+0.267X2-0.868X3-0.585X4-0.105X5+ 0.436X6+0.063X7+0.092X8+0.058X9+0.131X11-0.063X12	0.727	X3>X4>X6
2005	Whole basin	0.091-0.412X1+0.367X2+0.712X3+0.325X4+ 0.249X5+0.091X6+0.066X7+0.265X8+0.114X9-0.081X12	0.594	X3>X1>X2
	Agricultural area	0.073-0.209X1-0.147X2+0.700X3-0.354X4 +0.358X6+0.084X8-0.389X9-0.050X10-0.146 X11-0.049X12	0.670	X3>X9>X6
	Agro-pastoral area	0.092-0.426X1+0.424X2+0.726X3-0.216X4 +0.093X6-0.177X7+0.213X11-0.077X12	0.610	X3>X1>X2
	Pastoral area	0.089-0.150X1+0.460X2+0.771X3-0.150X4 +0.100X6+0.238X8+0.105X11-0.134X12	0.615	X3>X2>X8
2010	Whole basin	0.074-0.403X1+0.193X2+0.796X3-0.654X4- 0.118X5+0.204X6-0.058X7+0.101X8-0.057 X11-0.058X12	0.722	X3>X4>X1
	Agricultural area	0.091-0.490X1+0.094X2+0.698X3-0.512X4- 0.149X5+0.112X6+0.068X8-0.364X9-0.181 X11-0.075X12	0.685	X3>X4>X1
	Agro-pastoral area	0.056+0.583X3-0.722X4-0.549X5+0.055X6- 0.072X7+0.173X8-0.066X9+0.210X11-0.109 X12	0.615	X4>X3>X5
	Pastoral area	-0.096-0.201X1+0.189X2+0.547X3-0.240X4+ 0.223X5+0.148X6+0.078X7+0.216X8+0.067X11	0.592	X3>X4>X5
2015	Whole basin	0.092-0.298X1+0.299X2+0.549X3-0.165X4 +0.229X6-0.100X7+0.236X8-0.158X9-0.132 X11-0.101X12	0.610	X3>X2>X1
	Agricultural area	0.069-0.108X2+0.582X3-0.492X4-0.205X5 +0.345X6+0.114X8+0.305X9-0.137X11	0.718	X3>X6>X2
	Agro-pastoral area	0.025-0.302X1+0.215X2+0.722X3-0.189X7 +0.154X8-0.116X9-0.053X10+0.182X11-0.108X12	0.533	X3>X1>X7
	Pastoral area	0.024+0.123X2+0.556X3-0.375X4-0.225X5 +0.242X6-0.165X8+0.197X11-0.058X12	0.660	X3>X4>X6
2019	Whole basin	-0.070-0.514X1+0.256X2+0.683X3-0.138X5 +0.486X6-0.073X7+0.225X8-0.145X9-0.076 X10-0.156X11-0.133X12	0.703	X3>X1>X6
	Agricultural area	0.036-0.245X1+0.646X3-0.173X4-0.085X5 +0.442X6-0.051X7+0.052X8+0.367X9-0.044 X10-0.124X11	0.682	X3>X6>X9
	Agro-pastoral area	0.091+0.286X2+0.551X3-0.219X5+0.169X8 +0.085X10-0.114X11-0.112X12	0.589	X3>X2>X5
	Pastoral area	-0.024-0.322X1+0.483X2+0.621X3+0.166X6- 0.158X7+0.162X8-0.05X9-0.064X10+0.202X11 -0.177X12	0.676	X3>X2>X1

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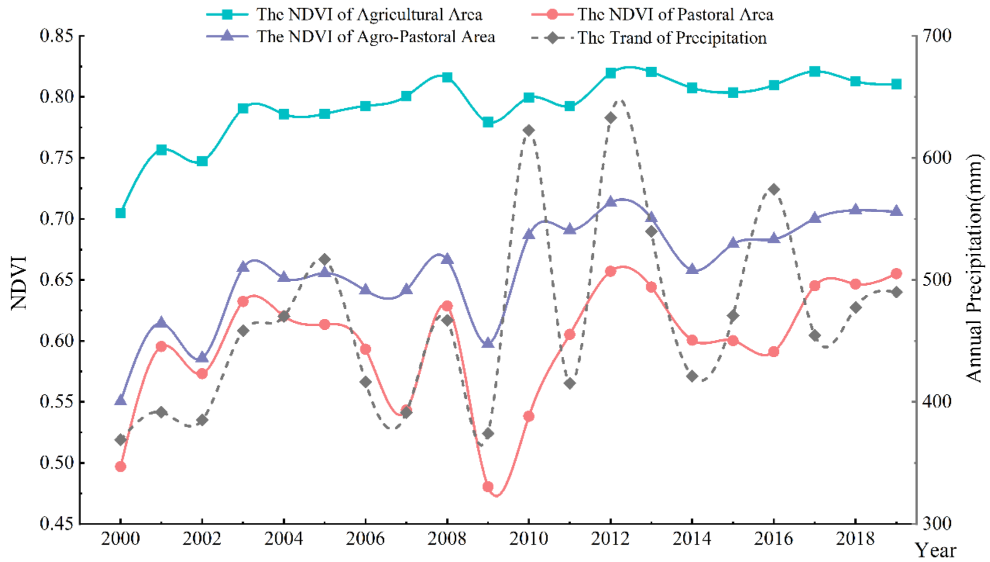

Figure 8. *Relationship between NDVI and precipitation in different regions*

However, the fluctuation of NDVI with precipitation in the agricultural area was significantly smaller than that in the pastoral area (*Figure 9*). We found that the regression coefficients of socioeconomic factors ranked in the top three among the variables in the best regression equations for agricultural areas in most years (see *Table 4*). It might be that the NDVI in the agricultural area was dominated by artificial crops. Compared with the pastoral area, human agricultural planting activities in the agricultural area were more active, and their positive contribution to NDVI was greater than the negative destructive impact of human production and construction. Reasonable agricultural activities and human intervention have resulted in less fluctuation of NDVI in the agricultural area.

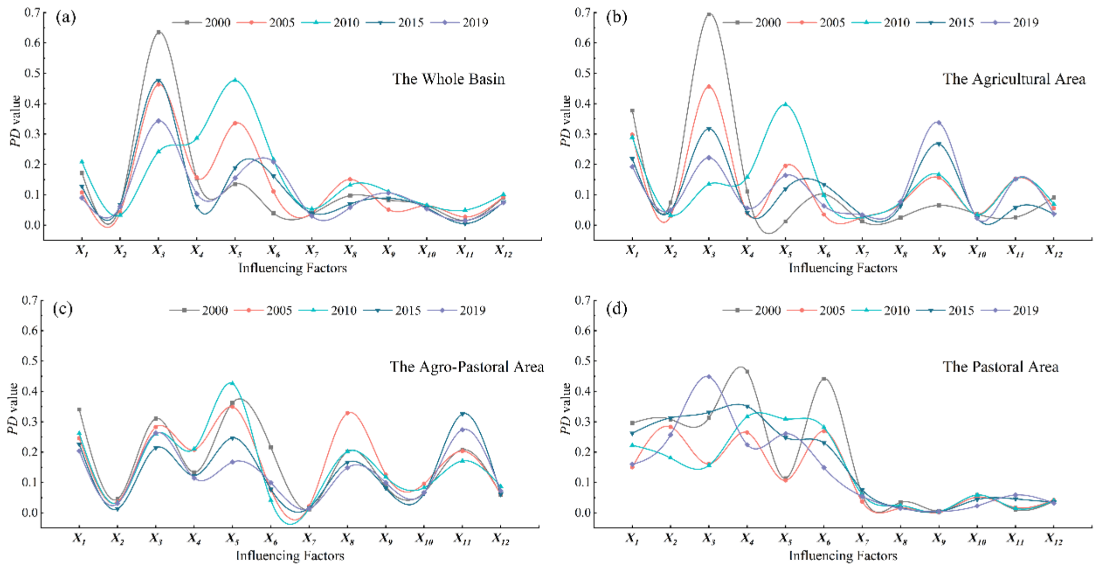

Figure 9. *The trends of PD values of influencing factors in different regions,2000-2019*

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Analysis of geo-detector results

Independent influences of factors on NDVI

The factor detector was employed to assess the impact of each environmental factor on NDVI by calculating the PD values for each factor (*Table 5*). From 2000 to 2019, the magnitude of the influence of environmental factors on NDVI throughout the basin was in the following order: X_3(precipitation) > X_5(solar radiation) > X_6(wind speed) >X_1(elevation) > X_9(nighttime lights) > X_{12}(distance to roads) > X_8(population density) > X_2(slope) > X_4(temperature) > X_{10}(distance to settlements) > X_7(distance to rivers) >X_{11} (GDP). Specifically for each functional area in the basin, the top three influencing factors were: precipitation, night light and elevation (agricultural area); solar radiation, elevation, and precipitation (Agro-Pastoral area); and temperature, precipitation, and slope (pastoral area).

Table 5. *The mean PD values of influencing factors from 2000 to 2019 in study area*

Factors	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X12
Whole basin (PD)	0.13	0.07	0.48	0.06	0.19	0.16	0.04	0.07	0.09	0.06	0.08
Agricultural area (PD)	0.22	0.05	0.32	0.04	0.12	0.13	0.03	0.06	0.27	0.02	0.04
Agro-pastoral area (PD)	0.23	0.01	0.21	0.12	0.25	0.08	0.02	0.17	0.08	0.06	0.06
Pastoral area (PD)	0.26	0.31	0.33	0.35	0.25	0.23	0.08	0.02	0.01	0.04	0.04

From the perspective of the whole basin, the *PD* value of precipitation was the largest (0.48), and the contribution rate to vegetation change was more than 40%. Therefore, precipitation emerged as the primary factor influencing the NDVI, corroborating the findings of the regression analysis. The contribution of solar radiation to the NDVI ranked second, and the intensity of solar radiation directly determines the photosynthetic intensity of green vegetation, so solar radiation had a significant effect on the NDVI (He et al., 2022). In addition to precipitation and solar radiation, elevation and temperature also contributed greatly to the NDVI. The elevation range of the LHRB is 0-2083 m with a height difference of 2083 m. The great height difference leads to a large variation of temperature in the basin. Elevation played an important role in affecting vegetation change.

In the agricultural area, the *PD* value of night lights was also larger (0.27), which might be related to the strong human activities. The nighttime lights represent the intensity of human activities to a certain extent, and in the agricultural areas human activity had an important influence on vegetation change. In the pastoral area, the *PD* values of natural factors were all at the forefront, which made a great contribution to the change of vegetation. However, the explanatory powers of all the socio-economic factors were low, and their effects on NDVI were not significant. This might be the fact that most of the land use types in pastoral areas were desert, bare land, and grassland, with less disturbance from human activities.

Figure 9 showed the trend of *PD* values of influencing factors from 2000-2019. The interannual fluctuation of *PD* values of the influencing factors in the agricultural area had some fluctuations, but the overall variation was more regular. In contrast, in the pastoral area, the interannual fluctuations of the *PD* values of the influencing factors were fierce,

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especially the *PD* values of the natural factors fluctuated drastically and with less regularity. This might be related to the ecological structure of the two functional areas. The pastoral area itself was less affected by human activities, and coupled with the harsh ecological environment, the vegetation ecological structure of the whole system was relatively fragile. Nuanced external disturbances and self-changes, such as human activities and local climate change, could lead to damage or even changes in the ecology of the vegetation in the area, which in turn could lead to changes in the vegetation and the factors affecting it. On the contrary in the agricultural area, first of all, the geographical environment was superior, water and thermal conditions were better, coupled with the reasonable intervention of human activities, the ecological structure of vegetation community in the agricultural area was more stable, less susceptible to be disturbed by external factors.

Effects of factor interaction on NDVI

The explanation of spatial differences in NDVI by a single variable is not sufficient. The interaction detector can reveal the synergistic effects between factors on NDVI change. The results revealed that the interaction among most factors strengthened the impact of individual factors on NDVI, indicating a non-linear synergistic effect between two factors (*Figure 10*).

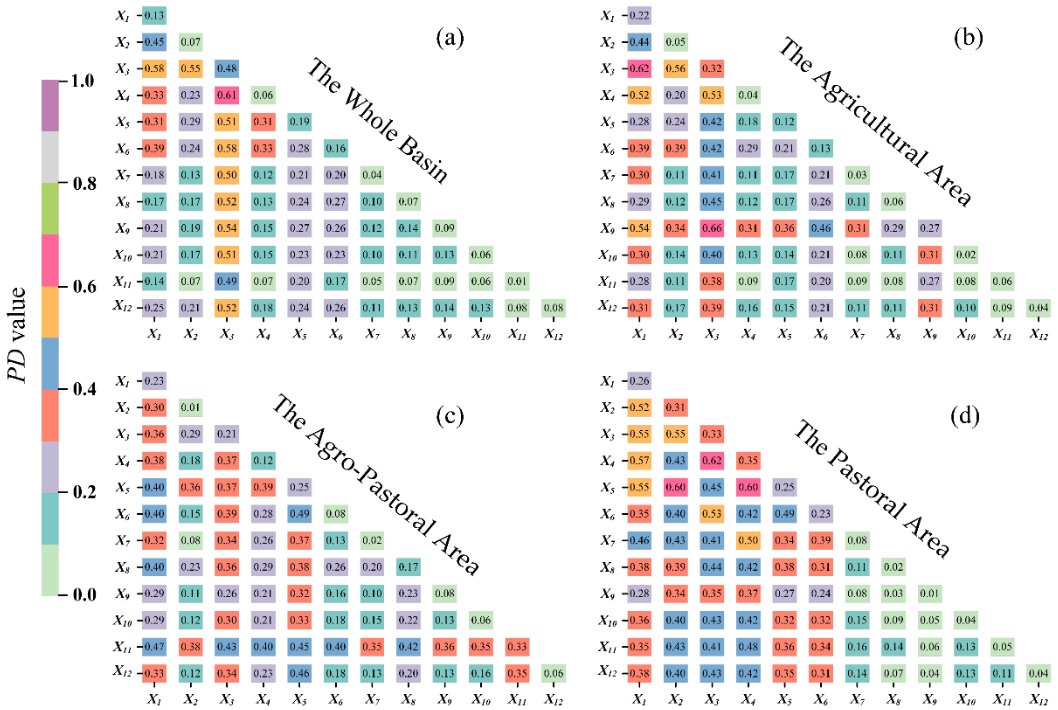

Figure 10. *The results of interactive detection in different regions*

In the whole basin, the interaction between precipitation and other environmental factors was the most significant (*Table 6*). The three largest sets of interacting factors were precipitation∩temperature, precipitation∩elevation, and precipitation∩wind speed, respectively. The interaction of natural factors, particularly the interaction between precipitation and temperature, played a dominant role in the whole basin. This interaction

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alone accounted for 61% of the observed NDVI changes in the basin. In the agricultural area, the strongest interaction was precipitation and nighttime lights, and their interaction explained 66% of the change in NDVI across the region. This indicated that both natural factors and human activities acted simultaneously in the agricultural areas and significantly affected NDVI. In the Agro-Pastoral area, the greatest interaction was observed between solar radiation and wind speed, where the NDVI was greatly affected by natural factors. In the pastoral area, the highest interaction was precipitation and temperature, followed by solar radiation and temperature. Similar to the Agro-Pastoral area, NDVI in pastoral area was also mainly influenced by natural factors, with less human disturbance and influence on vegetation.

Table 6. *The dominant interactions in different regions*

PD ranking	Whole basin	Agricultural area	Agro-Pastoral area	Pastoral area
1st	X3∩X4 0.61	X3∩X9 0.66	X5∩X6 0.49	X3∩X4 0.615
2nd	X3∩X1 0.58	X3∩X1 0.62	X1∩X11 0.47	X4∩X5 0.60
3rd	X3∩X6 0.58	X3∩X2 0.56	X5∩X11 0.45	X2∩X5 0.60

Effect of precipitation gradient on the stability of NDVI

Both regression analysis and Geo-detector indicated that annual precipitation had the most significant effect on NDVI. This was also consistent with previous researches, which highlights the critical role of moisture as a limiting factor for vegetation growth. Vegetation is known to be highly responsive to variations in precipitation, making it more susceptible to changes in moisture availability compared to other factors (Lamchin et al., 2020). According to the natural breakpoint method, the annual precipitation was classified into four grades: 0-365.32 mm/year (Level 1), 365.32-447.50 mm/year (Level 2) 447.50-544.81 mm/year (Level 3) and 544.82-632.95 mm/year (Level 4), and the effects of other environmental factors on NDVI under different precipitation gradients were discussed.

Figure 11 demonstrated that during periods of low precipitation (Level 1), natural factors such as temperature and wind speed exhibited a dominant influence on NDVI fluctuations. With the increase of precipitation, there was a gradual transition from the arid pastoral and Agro-Pastoral area in the west to the more humid agricultural plains in the east, human activities were gradually more frequent, and the explanatory power of socio-economic factors on NDVI gradually became greater. In the eastern plain with the highest precipitation (Level 4), the soil is fertile, with a long history of human exploitation and a high degree of agricultural mechanization and intensification, making it an important commercial grain production base in China. Here the explanatory power of socioeconomic factors exceeded that of natural factors as the dominant factor of NDVI change.

Additionally, *Figure 11* illustrated that as precipitation levels increased, the PD value curve exhibited larger fluctuations, indicating heightened activity and influence of each factor. When precipitation was at a low level, the *PD* values of the explanatory power of other environmental factors were small, and the factor activity was not high; when precipitation kept increasing, the *PD* values of other factors also kept increasing, and the

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activity of explanation of vegetation change was high, and precipitation became an important catalyst on NDVI change. To gain a deeper understanding of the mechanism behind NDVI change, the regression equations were established between environmental factors and NDVI under different precipitation gradients, and their R^2 were shown in *Figure 11b*. The R^2 values indicated that the regression equations demonstrate an improved fit between various environmental factors and NDVI as precipitation increases. This proved that precipitation not only has a strong effect on NDVI by itself, but also has strong interactions with other environmental factors. Furthermore, the gradient of precipitation influenced the degree of explanation for vegetation change. As precipitation increased, the explanatory power of the factors became more active, leading to an improved fit between each factor and NDVI.

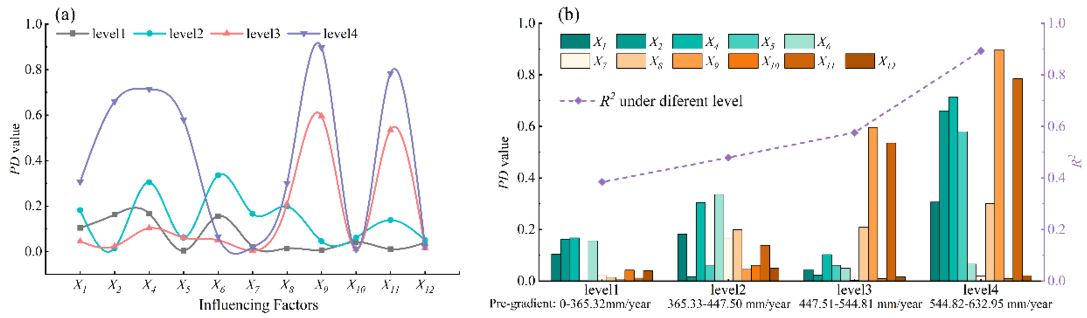

Figure 11. *PD values of influencing factors on NDVI along the gradient of annual precipitation*

Discussion

The analysis of vegetation change and driving factors is a hot issue in ecological research. Some scholars have studied the issue by different methods, such as correlation analysis (Lamchin et al., 2020) and residual analysis (Wang et al., 2015). The residual analysis method does not provide a quantitative measure of influential factors, while correlation analysis falls short in capturing the spatial variation of these factors. This paper introduces a novel approach by combining factor regression and factor interaction to comprehensively examine the impact of environmental factors on vegetation change, no one has used this method.

Spatial and temporal characteristics of NDVI

The LHRB, located in China's agricultural-pastoral interlacing zone, with a complex ecological environment due to its distinctive geographical location. In recent years, the vegetation in LHRB has changed significantly, showing a yearly upward trend, and the R^2 is shown in *Figure 5b*. This also coincides with previous studies in northern and southern China. For example, Lin confirmed that the vegetation in northern China has been recovering over the past 30 years (Lin et al., 2020). Fan also reported that 94.9% of the vegetation showed a rising trend in NDVI in the Poyang Lake basin from 2001-2015 (Fan et al., 2018).

The NDVI of the whole basin showed a gradual decreasing pattern from east to west. The central and western parts of the basin have a temperate continental climate with arid climate and scarce precipitation, while the eastern part is influenced by ocean monsoon and rich in water vapor. Different sources of water vapor in the east and west lead to an

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increasing trend of tropospheric precipitation from west to east. This was an important factor leading to more vegetation in the east and less vegetation in the west. In the past 20 years, the average value of NDVI in the LHRB was 0.69, and the overall vegetation cover level was high. The bare ground vegetation, low vegetation, medium vegetation, medium-high vegetation, and high vegetation accounted for 0.34%, 14.77%, 23.53%, 25.35% and 35.51% of the total area of the whole basin, respectively. The low and medium vegetation was mainly concentrated in the central and western pastoral and Agro-pastoral area, while the high vegetation was mainly concentrated in the agricultural plains in the east.

The NDVI in the LHRB has shown an overall increasing trend in the past 20 years, and the rank of the variation in descending order was: pastoral area > Agro-Pastoral area > agricultural area. The rising trend in pastoral areas is the most significant, which may have some correlation with a number of ecological projects and policies implemented by national and local governments in recent years. For example, implementing the policy of moving herdsmen to valley areas will help reduce grazing pressure on grassland and promote the development of vegetation in a positive direction (Bum, 2018). In addition, the implementation of measures such as the consolidation of mining, hydropower and tourism projects has also contributed to the recovery of vegetation. The trend of NDVI in the agricultural areas was the most stable, which probably be that the eastern Liaohe Plain, as an important food production base in China, is overwhelmingly vegetated with human-grown crops, and the cultivation activities are more regular, so the vegetation changes are more stable.

Analysis of the driving forces of NDVI change in the LHRB

The process of NDVI change is intricate and influenced by a combination of natural factors and human activities. It is crucial to quantify the factors that influence NDVI and determine the dominant ones, as this information can serve as a valuable reference for decision-makers. In this study, we employed factor regression and factor interaction techniques to investigate the drivers of NDVI in the LHRB from 2000 to 2019.

Factor explanation for NDVI change by single factors

The findings from the linear regression analysis demonstrated that the natural factors had a higher explanatory power on NDVI compared to the anthropogenic factors across the entire basin, among which precipitation was the most significant. This is consistent with the studies of Yu et al. (2020) and Zhan et al. (2022). In contrast, Liu et al. (2019) and Niu et al. (2021) considered temperature as the main factor affecting NDVI change in northern China. The difference in results may be attributed to differences in the selected NDVI dataset or differences in the study years. in addition, there was a conspicuous synchronization between the trend of precipitation and NDVI, and the trend of synchronization was the most obvious in the pastoral area. The main land types in the pastoral area were grassland and desert, with less human interference, and the vegetation change was mainly influenced by natural factors. Due to the poor climatic environment in this area, the community structure was simple, and the vegetation was susceptible to climate change, especially to the change in precipitation. The impact of precipitation on vegetation growth in the pastoral area showed a stronger response compared to other natural factors, which aligns with existing research findings. As the main factor on NDVI in the region, the fluctuation of precipitation directly affects the changing trend of NDVI, so the two have a stronger synchronization.

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The results of factor detection revealed that natural factors exhibited greater explanatory power than anthropogenic factors in relation to vegetation change across the entire basin. The *PD* values of the influencing factors from large to small were as follows: X_3(precipitation) > X_5(solar radiation) > X_6(wind speed) >X_1(elevation) > X_9(nighttime lights) > X_{12}(distance to roads) > X_8(population density) > X_2(slope) > X_4(temperature) > X_{10}(distance to settlements) > X_7(distance to rivers) >X_{11} (GDP). Precipitation was the main factor affecting NDVI in the LHRB from 2000 to 2019, which was consistent with the results of regression analysis. However, the explanatory power of each factor was different in different functional areas within the basin. The explanatory power of anthropogenic factors in the agricultural areas has been enhanced, while natural factors still occupied a dominant position in the pastoral and Agro-Pastoral area. In addition, we also found that the degree of fluctuation of the explanatory power curve of the factor in the pastoral areas was significantly higher than that in the agricultural areas, which may be related to the more fragile ecological structure of pastoral areas. The pastoral area itself was less affected by human activities, coupled with the bad ecological environment, the vegetation ecological structure of the whole system was relatively fragile. Small external disturbances and self-change, such as human activities and local climate change, may cause change or even destruction of the vegetation ecology in the area, which in turn may lead to changes in the factors affecting the vegetation.

In addition to the factors mentioned above, as an important food production base in China, the impact of agricultural production on vegetation cover in the region should not be underestimated. For example, the proportion of different crops may significantly affect annual NDVI in the region. Wheat, corn, and soybeans are the main crops in the region, with the area planted with corn increasing significantly in recent years. Corn has a high water demand and is mostly planted in areas with good irrigation conditions, such as the middle and lower reaches of the Laoha River, the middle reaches of the Xiliao River, and the banks of the Taizi River, which are also areas of high vegetation cover. The residual stalks after the corn harvest can be converted into soil fertilizer, enhancing soil fertility, which to some extent promotes crop growth and improves regional vegetation cover.

Factor explanation for NDVI change by interaction

The results of factor interaction showed that the interaction of any two factors showed a mutual promotion and nonlinear enhancement. This suggests that vegetation change is influenced not only by individual factors but also by the combined effects of multiple factors. The interaction between precipitation and other environmental factors exhibited the highest significance across the entire basin. The three largest groups of interacting factors were precipitation ∩ temperature, precipitation ∩ elevation, and precipitation ∩ wind speed. The interaction of natural factors played a dominant role throughout the basin. Our result is consistent with recent studies in which Zhang explored the factors influencing vegetation change in the Qilian Mountains over 20 years using the Geo-detector model (Zhang et al., 2021). The result indicated that the interaction of precipitation and temperature was the main cause for regional vegetation differences. This interaction was more pronounced in the long-time variation of vegetation.

Specifically for each functional area in the basin, the greatest interactions between pastoral and Agro-pastoral areas were precipitation ∩ temperature and solar radiation ∩ wind speed, respectively, and the interaction of natural factors had a greater effect on the vegetation in the region. In the agricultural area, the interaction between precipitation and night light is the strongest, and their interaction explained 66% of the vegetation change

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in the whole region. This indicated that a combination of natural and human factors significantly affected the vegetation change within the agricultural area. From the perspective of ecosystem complexity, it is rare for ecological issues to be caused by single factors alone, and the changes in NDVI are the outcome of a multifactorial combination. The feedback of natural and human activities on NDVI change is complicated. This was well illustrated by the result of the factor interactions, which also reminded us of the need to study the deeper drivers of vegetation change from a systematic perspective.

Comparison between factor regression and factor interaction

Both the regression model and factor detection consistently demonstrated that precipitation played a dominant role in influencing the NDVI in the LHRB. However, only in terms of the ranking of the explanatory power of each factor, the results of the geographic detector were different from the regression analysis (*Figure 12*), because the global optimal selection discarded the factors with logical relationships from the perspective of function fitting. For example, factor detection showed that both precipitation and solar radiation had significant explanatory power for the spatial distribution of NDVI in the agricultural area (*Figure 12*), but the regression coefficients of the two factors differed significantly in the regression model to make the function fit better. That is, the best regression model selection is only an optimal function that simulates the characteristics of the dependent variable, and its explanatory effect is sometimes not exactly equivalent to the driven explanation of the dependent variable.

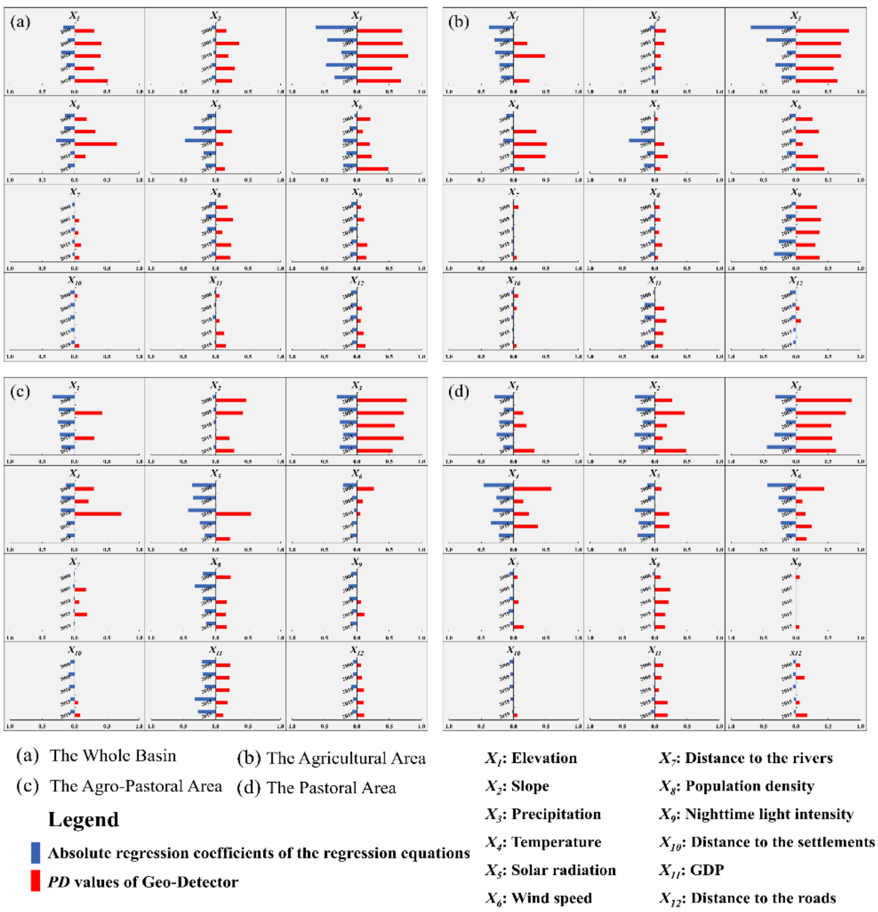

Figure 12. *Comparison of the results between linear regression and Geo-detector*

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While regression analysis provides insights into the individual influence of each factor, it may not adequately capture the interactions among factors and may have limitations in explaining complex relationships. In contrast, Geo-detector is a suitable method for studying NDVI change as it considers factor interactions and utilizes spatial stratification to reveal driving forces. However, Geo-detector also has its limitations. It cannot determine the positive or negative correlation of influencing factors and lacks the capability of the regression model to fully simulate the characteristics of the dependent variable.

Interpretation of precipitation gradients for driving system stability

Precipitation is considered to be the most significant climatic factor affecting the distribution and change of vegetation (Guerschman et al., 2020). This study further confirmed that precipitation played a crucial role as a limiting factor in vegetation dynamics. The gradient changes in precipitation influenced the interpretation power of NDVI by other factors (Zhu et al., 2020). In the central and western parts of the LHRB, precipitation was scarce, and the climate was arid, natural factors were the dominant factors influencing vegetation change, but at this time, the explanation power of each factor was low. The Horqin sand in the central part of the basin is in an area with low vegetation cover, which has not been improved because of the extreme hydrothermal conditions for many years (*Figure 6*). And as precipitation continuously increased, in the eastern of the study area, with a long history of cultivation and frequent human activities, the explanatory power of anthropogenic factors became stronger and surpasses other natural factors to become an important factor influencing vegetation change. The explanatory power of all factors was greater at this time, and the increase in precipitation also catalyzed the activity of other factors. With as precipitation continuously increased, the fit of each factor to NDVI became better and better.

Influence of human activities on NDVI

Although natural factors have a significant influence on vegetation change, the influence of human activities cannot be ignored. There are two main effects of human activities on vegetation dynamics: the positive effect promotes vegetation recovery (Zhang et al., 2016) and the negative effect leads to vegetation degradation (Yu et al., 2021). We noted that for some areas, such as around cities in the eastern plain, there was no conspicuous correlation between vegetation changes and natural factors, and anthropogenic factors (such as urban expansion, land use change) may have a stronger influence. The destructive construction activities have led to the vegetation degradation in these areas (*Figure 6*). This result is paralleled to previous researches. Those showed that vegetation degradation was more severe close to the central cities (Mu et al., 2022). And in certain grassland areas within the pastoral and Agro-pastoral region, the notable increase in vegetation trend can be attributed to the implementation of ecological policies and practices over the past two decades. These findings emphasize the importance of considering both climatic variables and human activities in vegetation management and promoting sustainable development in grassland ecosystems. Reasonable human activities will promote vegetation growth, and human activities had generally been dominated by positive effects in the LHRB. We expect that the NDVI in the LHRB will continue to increase in the future if such reasonable human activities can be maintained.

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Limitations and future perspectives

The acknowledgment of limitations in this study is essential for further improvement and future research. Indeed, the consideration of underlying factors in this study may not be exhaustive, indicating the need to include additional factors such as the implementation of ecological engineering projects, changes in land use patterns, time-delay effects of climate change on vegetation growth, and socio-economic factors. Expanding the scope of factors will help to reduce uncertainties and provide a more comprehensive understanding of vegetation dynamics. Furthermore, vegetation change is a complex process involving the interaction of multiple factors, and this study focused on the interaction of two factors. Future studies should delve into the effects of multi-factor interactions on vegetation change and increase the grid resolution to obtain a more nuanced understanding of the dynamics.

Conclusion

Based on NDVI data and some topographic, climatic, and human activity thematic data, this paper explored the vegetation change and its driving mechanisms in the LHRB, China from 2000 to 2019. The main conclusions are as follows.

(1) The NDVI in the LHRB has shown an overall increasing trend in the past 20 years, and the increasing degree is ranked from large to small: pastoral area > Agro-Pastoral area > agricultural area. The high cover vegetation (0.8-1) was the main interval of vegetation change in the whole basin, and the range of vegetation change has gradually decreased over the past 20 years. The coverage area of each grade tended to be stable.

(2) The results of linear regression showed that the natural factors explanatory on NDVI was greater than the anthropogenic factors throughout the basin, among which precipitation was the most significant. At the same time, there was a noteworthy synchronization between the trend of precipitation and vegetation, and the trend of synchronization was the most obvious in the pastoral area.

(3) Factor detection revealed that the *PD* values of the influencing factors from large to small were as follows: X_3(precipitation) > X_5(solar radiation) > X_6(wind speed) >X_1(elevation) > X_9(nighttime lights) > X_{12}(distance to roads) > X_8(population density) > X_2(slope) > X_4(temperature) > X_{10}(distance to settlements) > X_7(distance to rivers) >X_{11} (GDP). In the past 20 years, precipitation was the dominant factor affecting NDVI in the LHRB, which was consistent with the results of regression analysis.

(4) The results of factor interaction showed that the interaction of any two factors showed a mutual promotion and nonlinear enhancement. The three largest groups of interacting factors were precipitation∩ temperature, precipitation∩ elevation, and precipitation∩ wind speed. The interaction of natural factors played a dominant role throughout the basin.

(5) Precipitation was a key limiting factor affecting vegetation distribution, and the gradient changes in precipitation influenced the interpretation degree for NDVI by other factors. Furthermore, with the increase in precipitation, the fit of each factor to NDVI improved.

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REFERENCES

[1] Aho, K., Derryberry, D., Peterson, T. (2014): Model selection for ecologists: the worldviews of AIC and BIC. – Ecology 95: 631-36.
[2] Chen, W., Li, A. J., Hu, Y. G., Li, L. H., Zhao, H. M., Han, X. R., Yang, B. (2021): Exploring the long-term vegetation dynamics of different ecological zones in the farming-pastoral ecotone in northern China. – Environmental Science and Pollution Research 28: 27914-32.
[3] Di Gangi, L., Lapucci, M., Schoen, F., Sortino, A. (2019): An efficient optimization approach for best subset selection in linear regression, with application to model selection and fitting in autoregressive time-series. – Computational Optimization and Applications 74: 919-48.
[4] Ding, Y. X., Li, Z., Peng, S. Z. (2020): Global analysis of time-lag and -accumulation effects of climate on vegetation growth. – International Journal of Applied Earth Observation and Geoinformation 92.
[5] Ding, Q., Shao, Z. F., Huang, X., Altan, O., Zhuang, Q. W., Hu, B. (2021): Monitoring, analyzing and predicting urban surface subsidence: A case study of Wuhan City, China. – International Journal of Applied Earth Observation and Geoinformation 102: 102422.
[6] Fan, X. W., Liu, Y. B. (2016): A global study of NDVI difference among moderate-resolution satellite sensors. – ISPRS Journal of Photogrammetry and Remote Sensing 121: 177-91.
[7] Fan, X. W., Liu, Y. B., Tao, J. M., Wang, Y., Zhou, H. (2018): MODIS detection of vegetation changes and investigation of causal factors in Poyang Lake basin, China for 2001-2015. – Ecological Indicators 91: 511-22.
[8] Fensholt, R., Proud, S. R. (2012): Evaluation of Earth Observation based global long term vegetation trends - Comparing GIMMS and MODIS global NDVI time series. – Remote Sensing of Environment 119: 131-47.
[9] Gao, L., Wang, X. F., Johnson, B. A., Tian, Q. J., Wang, Y., Verrelst, J., Mu, X. H., Gu, X. F. (2020): Remote sensing algorithms for estimation of fractional vegetation cover using pure vegetation index values: A review. – ISPRS Journal of Photogrammetry and Remote Sensing 159: 364-77.
[10] Gholami, H., Mohamadifar, A., Rahimi, S., Kaskaoutis, D. G., Collins, A. L. (2021): Predicting land susceptibility to atmospheric dust emissions in central Iran by combining integrated data mining and a regional climate model. – Atmospheric Pollution Research 12: 172-87.
[11] Guerschman, J. P., Hill, M. J., Leys, J., Heidenreich, S. (2020): Vegetation cover dependence on accumulated antecedent precipitation in Australia: Relationships with photosynthetic and non-photosynthetic vegetation fractions. – Remote Sensing of Environment 240: 111670.
[12] Guo, G. H., Li, K., Zhang, D. G., Lei, M. (2022): Quantitative source apportionment and associated driving factor identification for soil potential toxicity elements via combining receptor models, SOM, and geo-detector method. – Science of the Total Environment 830: 154721.
[13] He, L., Guo, J. B., Jiang, Q. N., Zhang, Z. Y., Yu, S. P. (2022): How did the Chinese Loess Plateau turn green from 2001 to 2020? An explanation using satellite data. – Catena 214: 106246.
[14] Herrmann, S. M., Didan, K., Barreto-Munoz, A., Crimmins, M. A. (2016): Divergent responses of vegetation cover in Southwestern US ecosystems to dry and wet years at different elevations. – Environmental Research Letters 11: 12.
[15] Hong, H. Y., Tsangaratos, P., Ilia, I., Liu, J. Z., Zhu, A. X., Xu, C. (2018): Applying genetic algorithms to set the optimal combination of forest fire related variables and model forest fire susceptibility based on data mining models. The case of Dayu County, China. – Science of the Total Environment 630: 1044-56.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_281307

[16] Klauenberg, K., Wubbeler, G., Mickan, B., Harris, P., Elster, C. (2015): A tutorial on Bayesian Normal linear regression. – Metrologia 52: 878-92.
[17] Lamchin, M., Wang, S. W., Lim, C. H., Ochir, A., Pavel, U., Gebru, B. M., Choi, Y., Jeon, S. W., Lee, W. K. (2020): Understanding global spatio-temporal trends and the relationship between vegetation greenness and climate factors by land cover during 1982-2014. – Global Ecology and Conservation 24: e01299.
[18] Li, H. W., Yang, X. P. (2014): Temperate dryland vegetation changes under a warming climate and strong human intervention - With a particular reference to the district Xilin Gol, Inner Mongolia, China. – Catena 119: 9-20.
[19] Liao, L. M., Song, J. L., Wang, J. D., Xiao, Z. Q., Wang, J. (2016): Bayesian Method for Building Frequent Landsat-Like NDVI Datasets by Integrating MODIS and Landsat NDVI. – Remote Sensing 8(6): 452.
[20] Lin, X. N., Niu, J. Z., Berndtsson, R., Yu, X. X., Zhang, L., Chen, X. W. (2020): NDVI Dynamics and Its Response to Climate Change and Reforestation in Northern China. – Remote Sensing 12(24): 4138.
[21] Liu, Y., Li, L. H., Chen, X., Zhang, R., Yang, J. M. (2018): Temporal-spatial variations and influencing factors of vegetation cover in Xinjiang from 1982 to 2013 based on GIMMS-NDVI3g. – Global and Planetary Change 169: 145-55.
[22] Liu, S. Y., Huang, S. Z., Xie, Y. Y., Wang, H., Huang, Q., Leng, G. Y., Li, P., Wang, L. (2019): Spatial-temporal changes in vegetation cover in a typical semi-humid and semi-arid region in China: Changing patterns, causes and implications. – Ecological Indicators 98: 462-75.
[23] Liu, H., Li, X. J., Mao, F. J., Zhang, M., Zhu, D., He, S. B., Huang, Z. H., Du, H. Q. (2021): Spatiotemporal Evolution of Fractional Vegetation Cover and Its Response to Climate Change Based on MODIS Data in the Subtropical Region of China. – Remote Sensing 13(5): 913.
[24] Ma, Z. H., Guo, J. H., Li, W. M., Cai, Z. Y., Cao, S. X. (2021): Regional differences in the factors that affect vegetation cover in China. – Land Degradation & Development 32: 1961-69.
[25] MacNab, Y. C. (2014): On identification in Bayesian disease mapping and ecological-spatial regression models. – Statistical Methods in Medical Research 23: 134-55.
[26] Mu, B. H., Zhao, X., Zhao, J. C., Liu, N. J., Si, L. P., Wang, Q., Sun, N., Sun, M. M., Guo, Y. K., Zhao, S. Q. (2022): Quantitatively Assessing the Impact of Driving Factors on Vegetation Cover Change in China's 32 Major Cities. – Remote Sensing 14(4): 839.
[27] Niu, B. B., Li, X. J., Li, F. Q., Wang, Y., Hu, X. (2021): Vegetation dynamics and its linkage with climatic and anthropogenic factors in the Dawen River Watershed of China from 1999 through 2018. – Environmental Science and Pollution Research 28: 52887-900.
[28] Palmate, S. S., Pandey, A., Kumar, D., Pandey, R. P., Mishra, S. K. (2017): Climate change impact on forest cover and vegetation in Betwa Basin, India. – Applied Water Science 7: 103-14.
[29] Pettorelli, N., Laurance, W. F., O'Brien, T. G., Wegmann, M., Nagendra, H., Turner, W. (2014): Satellite remote sensing for applied ecologists: opportunities and challenges. – Journal of Applied Ecology 51: 839-48.
[30] Schulz, J. J., Cayuela, L., Rey-Benayas, J. M., Schroder, B. (2011): Factors influencing vegetation cover change in Mediterranean Central Chile (1975-2008). – Applied Vegetation Science 14: 571-82.
[31] Shen, Q., Gao, G. Y., Lu, Y. H., Wang, S., Jiang, X. H., Fu, B. J. (2017): River flow is critical for vegetation dynamics: Lessons from multi-scale analysis in a hyper-arid endorheic basin. – Science of the Total Environment 603: 290-98.
[32] Song, Y. Z., Wang, J. F., Ge, Y., Xu, C. D. (2020): An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: cases with different types of spatial data. – GIScience & Remote Sensing 57: 593-610.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_281307

[33] Tian, Y. C., Bai, X. Y., Wang, S. J., Qin, L. Y., Li, Y. (2017): Spatial-temporal changes of vegetation cover in Guizhou Province, Southern China. – Chinese Geographical Science 27: 25-38.
[34] van Erp, S., Oberski, D. L., Mulder, J. (2019): Shrinkage priors for Bayesian penalized regression. – Journal of Mathematical Psychology 89: 31-50.
[35] Verbesselt, J., Hyndman, R., Newnham, G., Culvenor, D. (2010): Detecting trend and seasonal changes in satellite image time series. – Remote Sensing of Environment 114: 106-15.
[36] Wang, J., Wang, K. L., Zhang, M. Y., Zhang, C. H. (2015): Impacts of climate change and human activities on vegetation cover in hilly southern China. – Ecological Engineering 81: 451-61.
[37] Wang, J. F., Zhang, T. L., Fu, B. J. (2016): A measure of spatial stratified heterogeneity. – Ecological Indicators 67: 250-56.
[38] Wang, J., Xu, C. (2017): Geodetector: Principle and prospective. – Acta Geographica Sinica 72: 116-34.
[39] Wang, H. J., Li, Z., Cao, L., Feng, R., Pan, Y. P. (2021): Response of NDVI of Natural Vegetation to Climate Changes and Drought in China. – Land 10(9): 966.
[40] Wen, Z. F., Wu, S. J., Chen, J. L., Lu, M. Q. (2017): NDVI indicated long-term interannual changes in vegetation activities and their responses to climatic and anthropogenic factors in the Three Gorges Reservoir Region, China. – Science of the Total Environment 574: 947-59.
[41] Wu, D. H., Wu, H., Zhao, X., Zhou, T., Tang, B. J., Zhao, W. Q., Jia, K. (2014): Evaluation of Spatiotemporal Variations of Global Fractional Vegetation Cover Based on GIMMS NDVI Data from 1982 to 2011. – Remote Sensing 6: 4217-39.
[42] Yang, K., Sun, W. Z., Luo, Y., Zhao, L. (2021): Impact of urban expansion on vegetation: The case of China (2000-2018). – Journal of Environmental Management 291: 112598.
[43] Yu, H. C., Bian, Z. F., Mu, S. G., Yuan, J. F., Chen, F. (2020): Effects of Climate Change on Land Cover Change and Vegetation Dynamics in Xinjiang, China. – International Journal of Environmental Research and Public Health 17(13): 4865.
[44] Yu, L., Wu, Z. T., Du, Z. Q., Zhang, H., Liu, Y. (2021): Insights on the roles of climate and human activities to vegetation degradation and restoration in Beijing-Tianjin sandstorm source region. – Ecological Engineering 159: 106105.
[45] Zhan, C., Liang, C., Zhao, L., Jiang, S. Z., Niu, K. J., Zhang, Y. L., Cheng, L. (2022): Vegetation Dynamics and its Response to Climate Change in the Yellow River Basin, China. – Frontiers in Environmental Science 10: 892747.
[46] Zhang, Y., Zhang, C. B., Wang, Z. Q., Chen, Y. Z., Gang, C. C., An, R., Li, J. L. (2016): Vegetation dynamics and its driving forces from climate change and human activities in the Three-River Source Region, China from 1982 to 2012. – Science of the Total Environment 563: 210-20.
[47] Zhang, L. F., Yan, H. W., Qiu, L. S., Cao, S. P., He, Y., Pang, G. J. (2021): Spatial and Temporal Analyses of Vegetation Changes at Multiple Time Scales in the Qilian Mountains. – Remote Sensing 13(24): 5046.
[48] Zhang, Y. X., Sun, J. Y., Lu, Y. F., Song, X. Q. (2022): Influence of Anthropogenic Activities and Major Natural Factors on Vegetation Changes in Global Alpine Regions. – Land 11(7): 1084.
[49] Zhao, Y. H., Liu, L., Kang, S. Z., Ao, Y., Han, L., Ma, C. Q. (2021): Quantitative Analysis of Factors Influencing Spatial Distribution of Soil Erosion Based on Geo-Detector Model under Diverse Geomorphological Types. – Land 10(6): 604.
[50] Zheng, K., Wei, J. Z., Pei, J. Y., Cheng, H., Zhang, X. L., Huang, F. Q., Li, F. M., Ye, J. S. (2019): Impacts of climate change and human activities on grassland vegetation variation in the Chinese Loess Plateau. – Science of the Total Environment 660: 236-244.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_281307

[51] Zhong, L., Ma, Y. M., Xue, Y. K., Piao, S. L. (2019): Climate Change Trends and Impacts on Vegetation Greening Over the Tibetan Plateau. – Journal of Geophysical Research-Atmospheres 124: 7540-52.

[52] Zhu, Z. C., Piao, S. L., Myneni, R. B., Huang, M. T., Zeng, Z. Z., Canadell, J. G., Ciais, P., Sitch, S., Friedlingstein, P., Arneth, A., Cao, C. X., Cheng, L., Kato, E., Koven, C., Li, Y., Lian, X., Liu, Y. W., Liu, R. G., Mao, J. F., Pan, Y. Z., Peng, S. S., Penuelas, J., Poulter, B., Pugh, T. A. M., Stocker, B. D., Viovy, N., Wang, X. H., Wang, Y. P., Xiao, Z. Q., Yang, H., Zaehle, S., Zeng, N. (2016): Greening of the Earth and its drivers. – Nature Climate Change 6: 791-795.

[53] Zhu, L. J., Meng, J. J., Zhu, L. K. (2020): Applying Geodetector to disentangle the contributions of natural and anthropogenic factors to NDVI variations in the middle reaches of the Heihe River Basin. – Ecological Indicators 117: 106545.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2201_281307