

SPATIO-TEMPORAL VARIATION AND DRIVING FORCES OF FRACTIONAL VEGETATION COVER IN THE BEIJING-TIANJIN-HEBEI REGION, CHINA

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Abstract. Studying the vegetation variation in the Beijing-Tianjin-Hebei (BTH) region is important for protecting the environment and maintaining ecological security. Fractional vegetation cover (FVC) was used to investigate the spatio-temporal variation of vegetation in the region based on NDVI and climate data from 2010 to 2020. The results showed that there were spatial differences in FVC in the BTH region. High and medium to high FVC were mainly distributed in the northeast and southwest of the region, while medium and low to medium FVC were mainly distributed in the northwest, and low FVC was scattered in cities, rural and bare lands. The average FVC increased with fluctuations during the study period at a rate of 2.86% per 11 years. Beijing and Hebei had an increasing trend of FVC, while Tianjin had a different trend. The lowest FVC in the BTH region occurred in 2014 and 2015 due to the extreme drought. Precipitation, temperature, and human activities were the driving forces for FVC variation, among which human activities played the greatest role. FVC variation was more sensitive to precipitation than to temperature. This study can assist in providing a scientific reference for formulating policies for environment protection and ecological restoration in the region.

Keywords: *fractional vegetation cover (FVC), spatio-temporal variation, normalized difference vegetation index (NDVI), precipitation, temperature, human activities, the Beijing-Tianjin-Hebei (BTH) region*

Introduction

As an important component of the terrestrial ecosystem, vegetation plays a key role in the process of global carbon, water and energy transformation and exchange (Law et al., 2002; Duo et al., 2016). Regarding to the driving factors, vegetation is extremely sensitive to climate change and human activities, and is considered as a comprehensive indicator to reflect the change of natural and social environment (Nie et al., 2021; Xia et al., 2021). Under the multiple impact of global climate change and human activities, vegetation is undergoing a series of complex variation at different spatial scales, which will affect human living and social development directly or indirectly (Jones et al., 2009; Zhao et al., 2019; Verma, 2021; Adeleye et al., 2022; Lian et al., 2022). Therefore, the conditions of vegetation growth, dynamic changes, carbon absorbing, driving factors and feedback effects are paid great attention all the time (Yang et al., 2022).

Among the parameters reflecting vegetation quantity and quality, fractional vegetation cover (FVC) has been widely used to quantify the vegetation change on global or regional scales (Chen et al., 2019; Piao et al., 2020; Huang et al., 2021; Mao et al., 2022). With global warming, the FVC showed an increasing trend in long time series, especially in

the mid-latitude regions of northern hemisphere (Tucker et al., 2001). FVC has increased globally since 1981, which was caused by carbon dioxide fertilization on the global scale and other factors such as temperature, precipitation and human activity (Piao et al., 2020). Regionally, temperature, precipitation and human activity factors were the dominant driving factors for the increasing FVC in Karst region from 2001 to 2020 (Huang et al., 2021). Studies by global MODIS LAI data revealed a strikingly increase vegetation in China and India from 2000 to 2017 due to reasonable land-use management (Chen et al., 2019). More than 94% of the Yellow river basin regions in China showed that FVC increased by MODIS data in the 21 century, which was caused by the joint effects of global warming, increasing population and afforestation (Tian et al., 2021). Climate change and human activities contributed 45.78% and 54.22% to the normalized difference vegetation index (NDVI) change in the Loess Plateau in China from 2000 to 2016, respectively (Shi et al., 2021). Over 85% of the counties had significantly increasing NDVI in the Haihe river basin in China, and the mean contribution rates of human activities and climate change accounted for 27% and 28%, respectively (Yang et al., 2022). Therefore, the FVC variation had obvious regional differences and complex driving factors such as climate and human activity, etc. However, the relationship between FVC and driving factors are still unclear (Currás et al., 2012; Ma et al., 2019; Feng et al., 2023), which restricts the further understanding of FVC variation.

The Beijing-Tianjin-Hebei (BTH) region is not only the political and cultural center of China, but also the major economic core area of northern China. Vegetation plays an important role in the region's ecological security. Studies showed that warming and drying trend were obvious in the region due to the increasing temperature and decreasing precipitation (Zhe et al., 2020; Xu et al., 2021), which might have great impact on vegetation variation. There were many studies focusing on the vegetation dynamics of the region (Li et al., 2017, 2019; Zhao et al., 2019; Cao et al., 2021; Jiang et al., 2021), which revealed the vegetation variation temporally or spatially. However, spatio-temporal variation of the vegetation and the driving forces in BTH region are not clear, which limits the understanding of the regional vegetation dynamics. Therefore, studies were conducted to investigate the spatio-temporal vegetation variation in terms of FVC and the relationship between variation and driving factors in BTH region from 2010 to 2020. The results can reveal the spatio-temporal dynamics of vegetation and the driving factors, which can also provide scientific reference for formulating vegetation protection and ecological restoration policies in the important region.

Materials and methods

Study area and data

The BTH region is located in the northern part of North China Plain (113°27'~119°50'E, 36°05'~42°40'N) with about 2.16×10^5 km² of total area (*Fig. 1*). It is an important population agglomeration area. The terrain declines gradually from northwest to southeast. Plateaus, mountains, hills, basins, and plains are the main landforms. The region is a typical warm temperate continental monsoon climate with four distinct seasons. The average annual temperature and precipitation are 9.87 °C and 534 mm, respectively. Temperature decreases gradually from south to north. Precipitation is mainly concentrated in June and August, and decreases gradually from southeast to northwest. The main vegetation types include deciduous broad-leaved forest, coniferous forest, shrubs, herbs and crops.

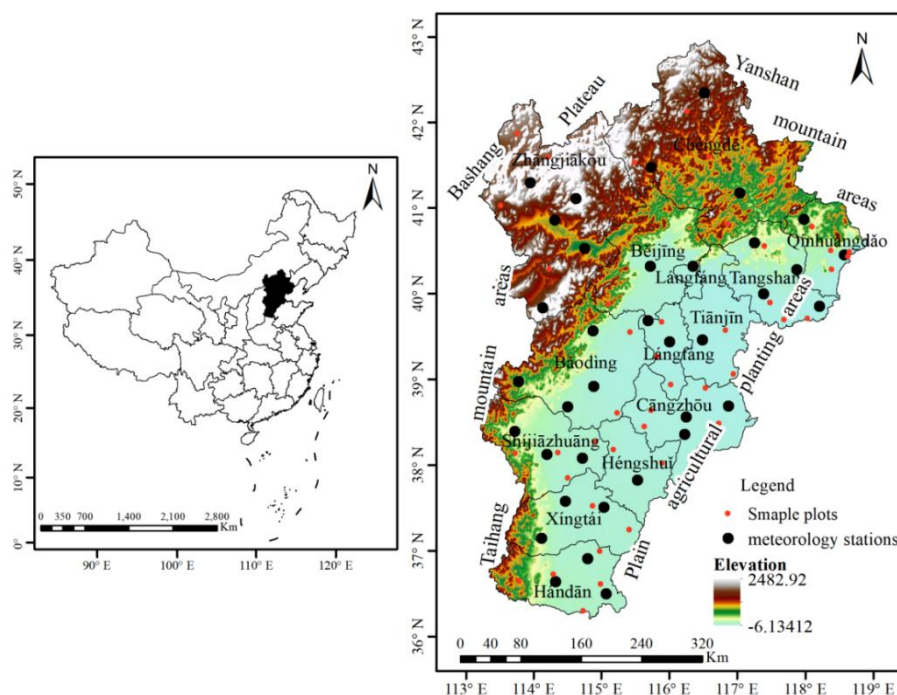


Figure 1. Location of the study area, meteorology stations and sample plots

NDVI of MODISMOD13Q1 data were obtained from NASA official website (<https://e4ftl01.cr.usgs.gov/>) with time and spatial resolution of 16 days and 250 m, respectively. The time from June to August was selected for highlighting the vegetation growth, which was considered as the best growing season of vegetation in the BTH region (Sun et al., 2012). MODIS Reprojection Tool (MRT) was used to extract the NDVI data. The NDVI data of each month after mosaic were tailored and projection conversion by ENVI5.6. Maximum value composites (MVC) were used to synthesize the monthly NDVI data during the growing season in order to eliminate the interference of clouds, oversaturation and other outliers (Thenkabail and Wu, 2012). Temperature and precipitation data of 36 meteorological observation stations were collected. The inverse distance weighting (IDW) interpolation method was used to produce the spatio-temporal grid maps of temperature and precipitation by ArcGIS 10.4, the resolution of which were resample to 250 m to fit the MOD13Q1 data.

Pixel dimidiante model

NDVI is the most effective index to reflect the vegetation growth and FVC. The principle of the pixel dimidiante model based on NDVI to calculate FVC was referred to the methods by relative studies (Hu et al., 2017; Yu et al., 2020; Yan et al., 2021; Dou et al., 2022). The calculation formula was as follows:

$$FVC = \frac{NDVI - NDVI_{soil}}{NDVI_{vegetation} - NDVI_{soil}} \quad (\text{Eq.1})$$

where FVC was the actual FVC value. $NDVI_{soil}$, $NDVI_{vegetation}$ were the NDVI values of pure vegetation and pure soil pixels, respectively. The values at the percentages of accumulated pixels of 3% and 97% NDVI were taken for both.

Combined with the threshold criteria of the above studies and the vegetation spatial distribution of the BTH region, FVC in the study was divided into low FVC, low to medium FVC, medium FVC, medium to high FVC and high FVC, which were (0–20%], (20–40%], (40–60%], (60–80%] and (80–100%], respectively. In order to verify the validation of the pixel dimidiate model based on NDVI data for FVC inversion, 40 typical and uniformly distributed field sample plots with 25 m × 25 m were selected in August 2021 in BTH region, including forest land, shrub land, herbaceous land, farmland and pure naked lands, and recording FVC, plant names, height, canopy density, etc. Meanwhile, the latitude and longitude of the sample plots were recorded by GPS. The measured FVC was evaluated by visual interpretation. The estimated FVC based on NDVI data from the inversion map were extracted according to the latitude and longitude of the sample plots, then the correlation between the estimated and measured FVC was calculated. There was high coefficient of determination ($r=0.9055$) between the measured and estimated value (Fig. 2), indicating that it was feasible to invert FVC by the pixel dimidiate model.

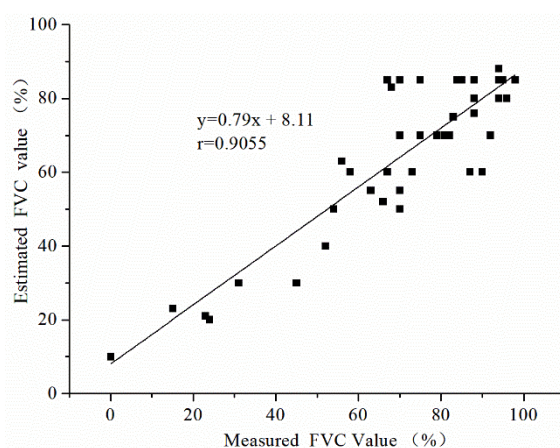


Figure 2. Correlation between the measured and estimated fractional vegetation cover (FVC)

Trend analysis of FVC

The least square method was adopted to analyze the trend of FVC by fitting the linear relationship between FVC and time at each pixel (Han et al., 2013; Mao et al., 2022). According to the testing results, the variation trend was divided into five grades: significant degradation (slope < 0, $p < 0.01$), obvious degradation (slope < 0, $0.01 < p < 0.05$), no change or stable ($p > 0.05$), obvious improvement (slope > 0, $0.01 < p < 0.05$), and significant improvement (slope > 0, $p < 0.01$).

Correlation analysis between FVC and precipitation, temperature

The correlation between FVC and precipitation, temperature was conducted by partial correlation analysis. Year grid data of regional precipitation and temperature were obtained through inverse distance weighting (IDW) interpolation according to the data of 36 meteorological observation stations, which were processed to be of the same resolution as FVC. Partial correlation coefficient between FVC and precipitation, temperature was calculated by Matlab16Ra software. The closer the coefficient was to 1, the greater correlation between them.

Analysis of temperature, precipitation and human activities on FVC change

Residuals were the difference between actual and predicted FVC values which were calculated by dimidiate pixel model and linear regression model, respectively (Li et al., 2012; Tong et al., 2016). The residuals could be used to quantify the impacts mechanism of human activities and temperature, precipitation on FVC change (Wang et al., 2018; Shi et al., 2021). Linear regression model between actual FVC and temperature, precipitation data was established to obtain predicted FVC values, which could indicate FVC change without human activities influence (Wang et al., 2009; Shi et al., 2021). Then the predicted FVC values were subtracted from the actual FVC values, and the results were residuals. If the residual value was 0, it could be considered to be attributable to temperature and precipitation. The positive residual value suggested that vegetation growing conditions were improving, it could be considered to be attributable to conservation, afforestation and restoration efforts by human activities (Wang et al., 2009, 2018), while the negative residual indicated the opposite.

The residual analysis method was based on the assumption that human activities remained stable, and only considered the impact of climate factors such as temperature and precipitation on FVC, and that there was a linear relationship between them. Taking temperature, precipitation as independent variables and FVC index as dependent variables, a linear regression model was constructed. The predicted FVC values were fitted by linear regression model, which were subtracted from the actual FVC values, and the results were residuals. The calculation formula was as follows:

$$\begin{aligned} F_{pre} &= ax_1 + bx_2 + c \\ \varepsilon &= F_{actual} - F_{pre} \end{aligned} \quad (\text{Eq.2})$$

where F_{pre} and F_{actual} were the predicted and actual FVC value, respectively. x_1 , x_2 were temperature and precipitation variables. a , b were the correlation coefficients, and c was a constant, ε was the residual.

Results

Spatial variation of FVC

There was obvious spatial heterogeneity of FVC in the BTH region during growing season. High and medium to high FVC accounted for 50.48% and 30.41% of the total areas, respectively (*Table 1*), and were mainly distributed in the northeast and southwest, including the Yanshan mountain areas, Bashang grasslands, Beijing mountain areas, Taihang mountain areas, and plain agricultural areas (*Fig. 3*). Medium and low to medium FVC accounted for 13.08% and 4.72%, respectively, and were mainly distributed in the northwest. Low FVC was 1.31% and scattered in cities, rural and bare lands.

According to the statistical analysis of FVC spatial distribution from 2010 to 2020, the transfer matrix in different types of FVC was calculated (*Table 1*). There was obvious transformation of FVC in the region with high, medium to high and medium FVC. Net increasing area with high FVC was 8507.17 km² during the study at a growth rate of 3.94%. While other FVC types showed net decrease at a decline rate of 1.96%, 1.07%, 0.66%, 0.25%, respectively. Therefore, the areas with high FVC kept an increasing trend and the vegetation growth conditions had been obviously improved in the BTH region.

Table 1. Fractional vegetation cover (FVC) types conversion matrix in the study area in 2010 and 2020

FVC types	2020							Ratio (%)	Transfer out
	LF	LMF	MF	MHF	HF	Total			
2010	LF	1505.67	1269.38	427.33	107.87	31.77	3342.02	1.56	1836.35
	LMF	635.82	4064.08	5085.37	1613.86	111.25	11510.38	5.38	7446.30
	MF	294.19	3040.86	11828.90	13305.50	1798.52	30267.97	14.14	18439.07
	MHF	228.13	1332.44	8533.17	34293.30	24885.60	69272.64	32.37	34979.39
	HF	138.83	383.70	2112.51	15763.70	81212.38	99611.12	46.55	18398.74
	Total	2802.64	10090.46	27987.28	65084.23	108039.52	214004.13		
Ratio (%)	1.31	4.72	13.08	30.41	50.48				
Transfer in	1296.97	6026.38	16158.38	30790.93	26827.14				
Ratio (%)	0.61	2.82	7.55	14.39	12.54				
Net value added	-539.38	-1419.91	-2280.69	-4188.41	8428.39				

LF: low fractional vegetation cover (FVC), LMF: low to medium FVC, MF: medium FVC, MHF: medium to high FVC, HF: high FVC

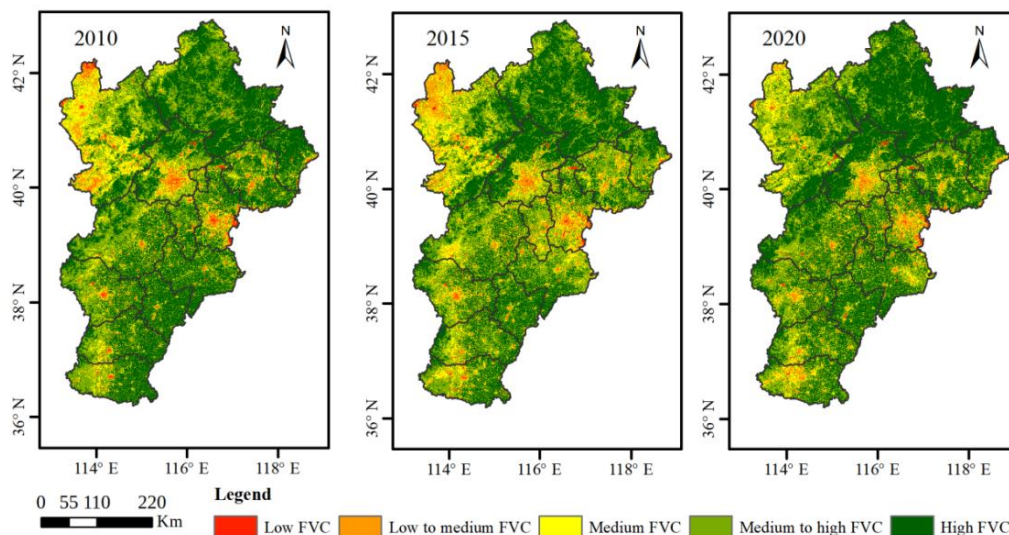


Figure 3. Average fractional vegetation cover (FVC) in the year of 2010, 2015, 2020 in the study area

Temporal variation of FVC

Generally, average FVC in BTH region increased with fluctuations by 73.77% in 2010 to 76.63% in 2020 with the average and at a rate of 74.72% and 2.86% per 11 years, respectively (Fig. 4). The curve of the average FVC during the growing season showed one trough and two peaks with an upward trend. Specifically, the rising years were 2010-2012 and 2015–2018, while the declining years were 2013–2015 and 2018–2019. The highest FVC appeared in 2018 with 78.06%, while the lowest in 2015 with 71.24%. From 2010 to 2020, the average FVC mainly concentrated in the high and medium to high FVC ranges, which accounted for 30.07% and 49.49% of the region, respectively (Table 2). FVC grades of low, low to medium and medium accounted for 1.74%, 5.23%, and 13.47%, respectively. Overall, the proportion of the area with a high FVC level

showed an increasing trend of 46.55% to 50.69% from 2010 to 2020, while the area proportion of other FVC levels showed downward trend. Besides, the FVC in BTH varied gradually to a higher level.

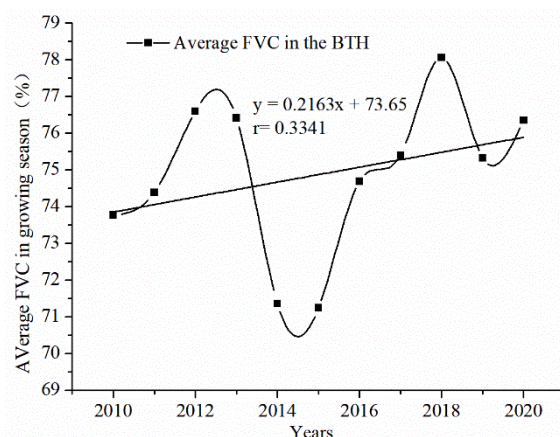


Figure 4. Average fractional vegetation cover (FVC) from 2010 to 2020 in the study area

Table 2. The area ratio of different fractional vegetation cover (FVC) levels in the growing season from 2010 to 2020 in the study area

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average
LF	1.56	1.69	1.74	1.47	1.94	1.49	3.31	1.89	1.36	1.31	1.35	1.74
LMF	5.38	5.30	4.33	4.16	7.51	7.00	5.71	5.23	3.72	4.72	4.51	5.23
MF	14.14	13.50	12.64	12.03	16.64	16.82	12.86	13.76	9.98	13.08	12.68	13.47
MHF	32.37	30.99	26.53	28.20	32.37	34.67	28.15	28.49	27.84	30.41	30.77	30.07
HF	46.55	48.53	54.77	54.14	41.54	40.02	49.97	50.63	57.10	50.48	50.69	49.49

LF: low fractional vegetation cover (FVC), LMF: low to medium FVC, MF: medium FVC, MHF: medium to high FVC, HF: high FVC

In terms of administrative region, average FVC in the growing season in Hebei was the maximum (76.05%), followed by Beijing (73.08%) and Tianjin (58.98%) in 2020. Average FVC in Beijing and Hebei increased with fluctuations from 2010 to 2020 at a rate of 3.37% per 11 years ($r = 0.4243$) and 1.50% per 11 years ($r = 0.2449$), respectively (Fig. 5). However, average FVC in Tianjin decreased with fluctuations at a rate of -3.30% per 11 years ($r = 0.2646$).

FVC trend analysis

According to the trend analysis of slope, 59.92% of FVC in the region showed an increasing trend, while 40.08% showed a decreasing trend at the 0.95 confidence intervals from 2010 to 2020 (Fig. 6). The significant increasing FVC was located in Zhangjiakou, Hebei Province, and the obvious distributed in the cities of Beijing and Chengde, Tangshan, Qinhuangdao in Hebei.

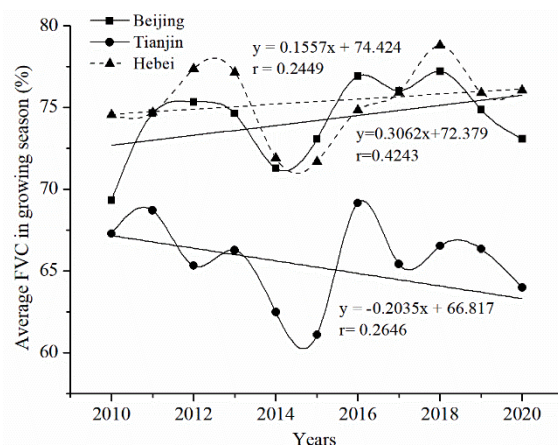


Figure 5. Average fractional vegetation cover (FVC) in the growing season from 2010 to 2020 in administrative regions

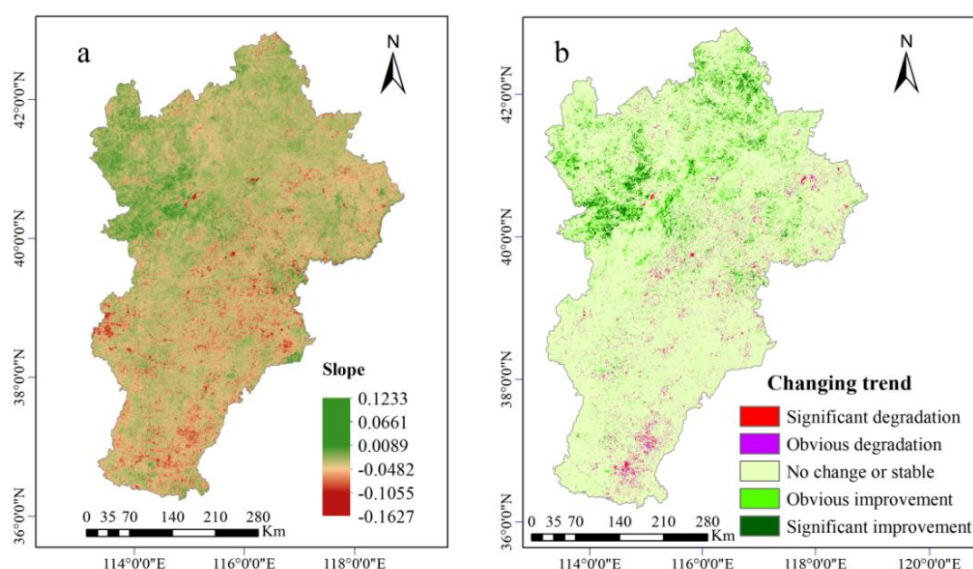


Figure 6. Trend and significance analysis in the study area. a, slope; b, changing trend

Relative analysis showed that areas of FVC with significant and obvious improvement accounted for 3.39% ($p < 0.01$) and 6.82% ($p < 0.05$), respectively (Table 3), while significant and obvious degradation accounted for 0.93% ($p < 0.01$) and 2.03% ($p < 0.05$), respectively. Meanwhile, 86.83% of the areas were not significant, showing no variation or being stable. The cities in BTH region also showed differences in FVC variation trend, which also indicated the spatial difference of FVC in the region.

Driving forces analysis of FVC variation

From 2010 to 2020, temperature in BTH region showed an increasing trend at a rate of 0.45°C per 11 years, while precipitation showed a decreasing trend at a rate of 7.85 mm per 11 years (Fig. 7). Comparison with the variation trend of FVC, temperature variation was basically consistent with that of FVC after 2015, while precipitation variation was highly consistent with FVC from 2010 to 2020 in general. Analysis showed that there

was significant positive correlation between FVC and precipitation ($r=0.676$, $p<0.05$), and near significant level between FVC and temperature ($r=0.601$, $p=0.05$), which further indicated that FVC was more sensitive to precipitation than to temperature.

Table 3. Variation trend of fractional vegetation cover (FVC) types in different districts of the study area

Districts	Unit	SD	OD	NCS	OI	SI	Total
Beijing	area/km ²	92.50	218.92	13135.96	2135.96	850.62	16433.96
	ratio/%	0.56	1.33	79.93	13	5.18	100
Tianjin	area/km ²	320.67	504.67	9850.07	450.01	232.94	11358.36
	ratio/%	2.82	4.44	86.72	3.96	2.05	100
Zhangjiakou	area/km ²	101.15	220.48	28621.75	5133.18	3019.46	37096.03
	ratio/%	0.27	0.59	77.16	13.84	8.14	100
Chengde	area/km ²	84.97	248.06	32729.14	4525.43	2327.13	39914.73
	ratio/%	0.21	0.62	82	11.34	5.84	100
Qinhuangdao	area/km ²	145.65	295.77	7221.28	140.28	50.13	7853.11
	ratio/%	1.85	3.77	91.95	1.79	0.65	100
Tangshan	area/km ²	132.37	282.84	11009.13	800.52	381.42	12606.26
	ratio/%	1.05	2.24	87.33	6.35	3.04	100
Langfang	area/km ²	108.92	232.27	5914.60	140.66	73.21	6469.66
	ratio/%	1.68	3.59	91.42	2.17	1.13	100
Baoding	area/km ²	207.41	471.33	20998.54	690.57	178.67	22546.52
	ratio/%	0.92	2.09	93.13	3.06	0.8	100
Cangzhou	area/km ²	113.47	321.87	13207.66	112.28	22.53	13777.82
	ratio/%	0.82	2.34	95.86	0.81	0.17	100
Shijiazhuang	area/km ²	93.51	272.49	13489.86	275.26	82.07	14213.19
	ratio/%	0.66	1.92	94.91	1.94	0.59	100
Hengshui	area/km ²	75.43	190.54	8560.08	88.52	17.85	8932.42
	ratio/%	0.84	2.13	95.83	0.99	0.2	100
Xingtai	area/km ²	235.86	523.64	11624.48	169.32	58.67	12611.96
	ratio/%	1.87	4.15	92.17	1.34	0.47	100
Handan	area/km ²	295.00	606.63	11204.44	69.62	14.44	12190.13
	ratio/%	2.42	4.98	91.91	0.57	0.12	100
Total	area/km ²	2006.90	4389.50	187567.00	14731.60	7309.13	216004.14
	ratio/%	0.93	2.03	86.83	6.82	3.38	100

SD, Significant degradation; OD, obvious degradation; NCS, no change or stable; OI, obvious improvement; SI, significant improvement

According to the correlation analysis between pixels, there were positive and negative correlations between FVC and precipitation and temperature, which with the partial correlation coefficient of 0.23 ($p<0.05$) and 0.12 ($p<0.05$), respectively. The proportions of positive and negative correlation coefficient pixel areas in the total pixel areas were 74.68% and 25.32% between FVC and precipitation, respectively (Fig. 8a), while between FVC and temperature were 65.78% and 34.22% between FVC and temperature, respectively (Fig. 9a). However, the areas with significant correlation between FVC and precipitation accounted for 10.92% of the total areas (Fig. 8b). Similarly, there was 6.61% showed significant correlation between FVC and temperature (Fig. 9b). In summary,

precipitation and temperature were both the main factors affecting vegetation growth and distribution in the BTH region. According to the quantified results, the variation trend residual of human activities increased at an average rate of 0.003 from 2010 to 2020 (Fig. 10), which indicated that human activities were continuous and beneficial for FVC increase. Positive value indicated that human activities promoted the increase of FVC by 53% of the total area. On the contrary, negative value implied decrease by 47%. The positive areas were mainly distributed in the cities of Beijing and Zhangjiakou, Chengde, Qinhuangdao, Tangshan in Hebei. However, the negative areas scattered in the cities of Tianjin and Handan, Xingtai, Hengshui, Shijiazhuang, Baoding, Langfang in Hebei. Besides, the average contribution rate of human activities was 62.76%, while precipitation and temperature was 37.24%. Overall, not only can human activities promote the increase of FVC, but also inhibit the increase rate.

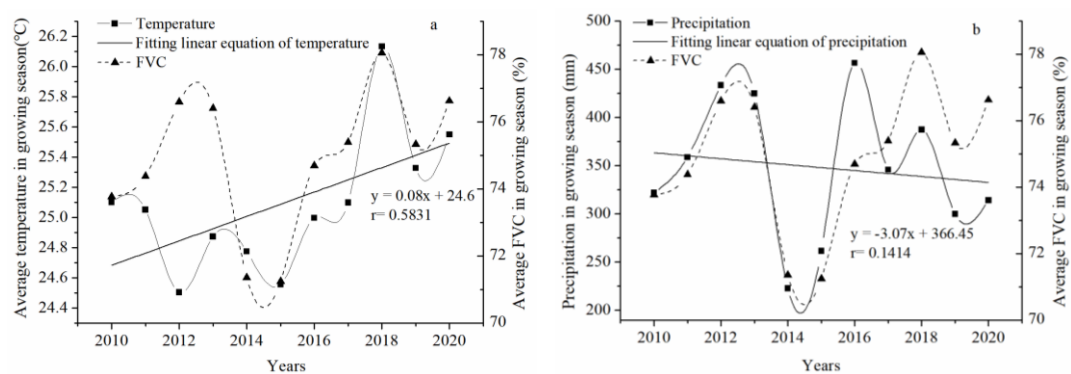


Figure 7. Annual variation of fractional vegetation cover (FVC), temperature and precipitation from 2010 to 2020. a, temperature and FVC; b, precipitation and FVC

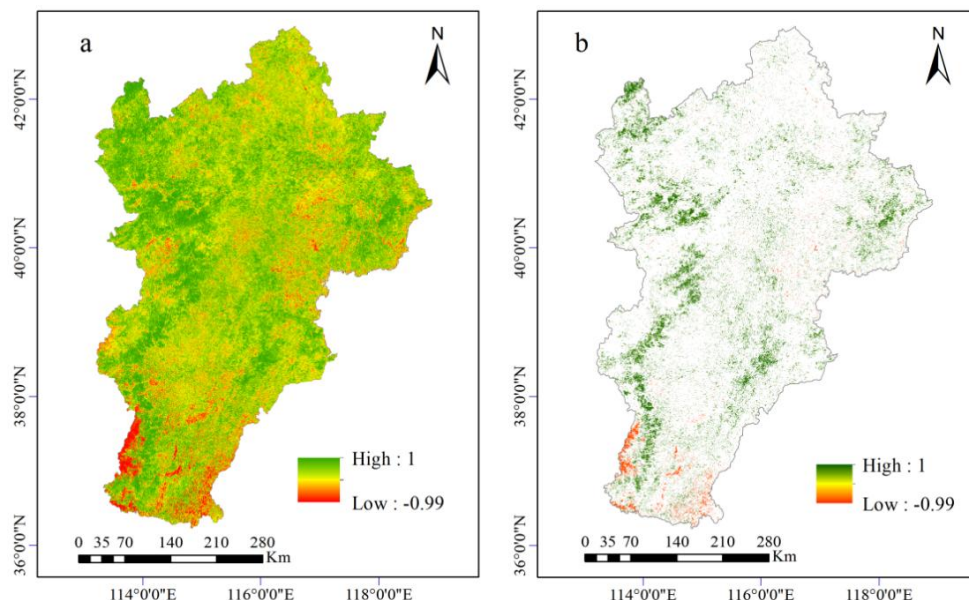


Figure 8. Correlation and t-test results between fractional vegetation cover (FVC) and precipitation from 2010 to 2020. a, correlation coefficient between FVC and precipitation; b, significant correlation between FVC and precipitation

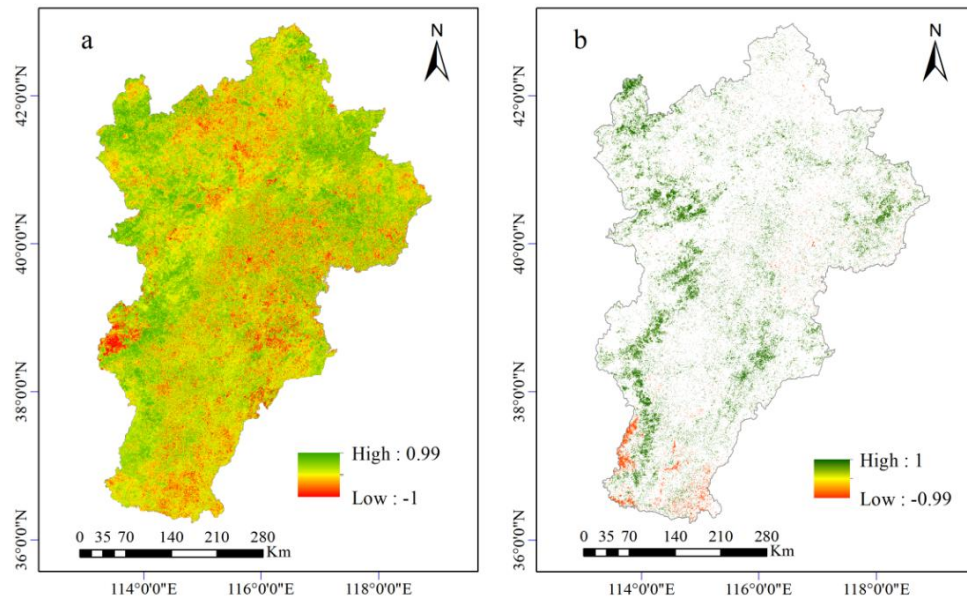


Figure 9. Partial correlation coefficient and t-test results between fractional vegetation cover (FVC) and temperature. a, correlation coefficient between FVC and temperature; b, significant correlation between FVC and temperature

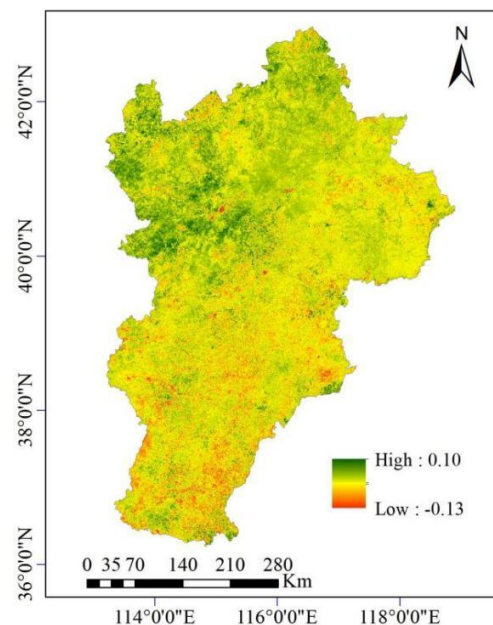


Figure 10. Variation trend of residual slope of human activities

Discussion

Spatio-temporal variation of FVC

FVC in the BTH region shows an obvious spatial heterogeneity and a landform type feature, which is in agreement with previous studies (Zhao et al., 2019). The areas with high FVC mostly distribute in the mountainous forest lands, Bashang grassland in Hebei, plain farmlands and wood lands. The areas are ecological red line zones and important

ecological restoration regions, which are needed high protection and few disturbance by human activities (Chi et al., 2018). Compared with the high FVC areas, the low FVC areas scatter in cities, rural and sandy regions in the northwest. Urban expansion, overgrazing and climate change were the main reasons for the low FVC (Deng et al., 2018; Chang et al., 2020; Luan et al., 2022).

In the temporal variation trend, the average FVC increases by 2.86% from 2010 to 2020. The overall vegetation in the region shows increasing tendency from 2000 to 2015 (Zhao et al., 2019), resulting in the increasing average FVC by 1.30% from 2001 to 2015 (Li et al., 2017) and 6.50% from 2005 to 2015 (Li et al., 2019). The differences between the studies are the time interval, data resource and study methods. However, the increasing trend of FVC in the BTH region is accordant, which may result from the implementation of ecological projects such as natural forest protection, afforestation and ecological restoration. Meanwhile, climate factors may also play an important role in the increasing FVC.

Impacts of precipitation, temperature and human activities

Among the climate factors, precipitation and temperature are the key to affect vegetation growth (Li et al., 2021). In the BTH region, precipitation and temperature are also the important factors impacting FVC due to the significant and near significant positive correlation between FVC and the two factors, respectively. Furthermore, the impact of precipitation on FVC variation is relatively higher than temperature, which in accordance with other studies in this region (Meng et al., 2015; Yan et al., 2019). However, based on a vegetation index derived from remote sensing for the BTH region through time, Jiang et al. (2021) also finds that temperature is the most influential factors among their climate variables by the Random Forest regression model to rank the importance of the climatic and anthropogenic factors. However, the regression model has been proven to exist overfitting problems on certain noisy classification or regression, and there may be many similar decision trees that obscure the true result (Pang et al., 2006).

On the other hand, the BTH region is an area of 216,000 km² with temperate semi-humid and semi-arid continental monsoon climate. There are differences among climate factors such as precipitation, temperature and solar radiation, which affect vegetation jointly and spatially. Among the factors, relative studies show that vegetation is more sensitive to precipitation than other factors in BTH region (Zou et al., 2022). There is extreme drought in 2014 and 2015, and results in the lowest FVC. Additionally, vegetation growth season may be extended in the BTH region with global warming, and it may be beneficial for vegetation growth under the condition that precipitation increases and meets the requirements of vegetation growth, which is needed for further investigation.

In addition to climate factors, human activities were also the important driving factors affecting vegetation growth and distribution (Kou et al., 2021). Economic development and urbanization in the BTH region occupy ecological space and farmland, posing a greater threat to vegetation space (Jiang et al., 2021). However, average FVC in the region increases from 2010 to 2020. As early as the 20th century, in order to protect the ecological environment in northern China, government has implemented numerous reforestation projects, such as the Beijing-Tianjin sand source control project and three north shelter forest program. Recently, since the collaborative development strategy for the BTH region is put forward, the three administrative regions have implemented a series

of ecological engineering projects, including optimizing ecological space, large-scale land greening, accurately improving forest quality, protecting and restoring important wetlands, establishing a national park system around the capital, establishing national reserve forests and protection farmland projects, and so on (Xu et al., 2021). Therefore, afforestation and ecological protection projects promote the increase of FVC. It is also confirmed by residual and contribution rate analysis. In terms of the vegetation evolution, the drastic fluctuation of vegetation in short period is mainly caused by human activity factors, supplemented by climate factors (Sun et al., 2021). According to the results of average contribution rate, the contribution of human activities to FVC variation is greater than precipitation and temperature during the study. However, Cao et al. (2021) finds the contrary result that contribution of climate factors to FVC is greater than human activities. The differences may be also due to the time interval, data resource and study methods.

In general, this study analyzes the spatio-temporal variation and driving forces of FVC in the BTH region. The results provide guidance for ecological protection, construction, restoration, and formulating regional coordinated development policies in the region. However, due to the fact that NDVI data in summer can reflect vegetation being in a lush period with good growth, its characteristics are obvious in remote sensing images and it is relatively easy to distinguish. This study only preliminarily explores the correlation between summer vegetation, temperature, precipitation, and human activities in the BTH region. The limitations may lead to certain uncertainties in evaluating the spatio-temporal variation of FVC. To improve the accuracy of the research, it is recommended to combine multi season NDVI data to more comprehensively reflect the dynamic changes in FVC. Meanwhile, although residual analysis is a commonly used method for separating climate factors and human activities on FVC, this study has a certain degree of uncertainty. The residual method is based on the assumption that there is a linear relationship between climate factors and FVC, which means that the residual analysis model performs best when FVC is linearly correlated with climate factors. But this assumption is only theoretically valid and difficult to hold in practice. Because in addition to precipitation, temperature and human factors, there are many complex factors such as solar radiation, wind, soil quality, and so on. Driving forces analysis of FVC variation also shows inconsistent patterns with correlation of temperature and precipitation, and residual variation trend of human activities, indicating that other factors also affect FVC. The influence and contribution of other factors are needed for further studies.

Conclusion

FVC shows spatio-temporal variation in the BTH region. High and medium to high FVC accounting for 80.89% the total areas mainly distributes in the northeast and southwest of the region, while medium and low to medium FVC mainly distributes in the northwest, and low FVC accounting for 1.31% scatters in cities, rural and bare lands. Average FVC increases with fluctuations at a rate of 2.86% per 11 years. 59.92% of FVC in the region showed an increasing trend which attributed to numerous reforestation projects implemented by government. Beijing and Hebei increase at a rate of 3.37% per 11 years and 1.50% per 11 years, respectively, while Tianjin decreases at a rate of -3.30% per 11 years. The lowest FVC in the region occurs in 2014 and 2015 due to the extreme drought. FVC variation is more sensitive to precipitation than to temperature. Impact of human activities on FVC variation is greater than climate factors due to the contribution rate of human activities is 62.76% while precipitation and temperature is 37.24%.

Therefore, spatio-temporal differences exist of FVC in the BTH region. Precipitation, temperature and human activities are the driving factors for FVC variation, in which human activities is greater. Further relative studies are needed for FVC variation to maintain ecological security in the BTH region.

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REFERENCES

- [1] Adeleye, M. A., Connor, S. E., Haberle, S. G., Ivory, S., Adeonipekun, P. A. (2022): Long-term drivers and timing of accelerated vegetation changes in African biomes and their management implications. – *Global Ecology and Biogeography* 31(8): 1643-1654.
- [2] Cao, W., Wu, D., Huang, L., Pan, M., Huhe, T. L. (2021): Determinizing the contributions of human activities and climate change on greening in the Beijing–Tianjin–Hebei region, China. – *Scientific Reports* 11(1): 21201.
- [3] Chang, Y. Y., Zhang, G. L., Zhang, T. Z., Xie, Z., Wang, J. X. (2020): Vegetation dynamics and their response to the urbanization of the Beijing–Tianjin–Hebei region, China. – *Sustainability* 12(20): 8550.
- [4] Chen, C., Park, T., Wang, X. H., Piao, S. L., Xu, B. D., Chaturved, R. K., Fuchs, R., Brovkin, V., Ciais, P., Fensholt, R., Tømmervik, H., Bala, G., Zhu, Z. C., Nemani, R. R., Myneni, R. B. (2019): China and India lead in greening of the world through land-use management. – *Nature Sustainability* 2(2): 122-129.
- [5] Chi, Y. Y., Xu, K. P., Wang, J. J., Zhang, L. P. (2018): Identifying regional ecological space in Beijing, Tianjin, and Hebei. – *Acta Ecologica Sinica* 39(23): 1-9.
- [6] Currás, A., Zamora, L., Reed, J. M., García-Soto, E., Ferrero, S., Armengol, X., Mezquita-Joanes, F., Marqués, M. A., Riera, S., Julià, R. (2012): Climate change and human impact in central Spain during Roman times: High-resolution multi-proxy analysis of a tufa lake record (Somolinos, 1280m asl). – *Catena* 89(1): 31-53.
- [7] Deng, Y., Jiang, W. G., Wang, W. J., Lu, J. X., Chen, K. (2018): Urban expansion led to the degradation of habitat quality in the Beijing–Tianjin–Hebei Area. – *Acta Ecologica Sinica* 39(12): 4516-4525.
- [8] Dou, X., Ma, X. F., Huo, T. C., Zhu, J. T., Zhao, C. Y. (2022): Assessment of the environmental effects of ecological water conveyance over 31years for a terminal lake in central Asia. – *Catena* 208: 105725.
- [9] Duo, A., Zhao, W. J., Qu, X. Y., Jing, R., Xiong, K. (2016): Spatio-temporal variation of vegetation coverage and its response to climate change in North China plain in the last 33 years. – *International Journal of Applied Earth Observation and Geoinformation* 53: 103-117.
- [10] Feng, X. J., Tian, J., Wang, Y. X., Wu, J. J., Liu, J., Ya, Q., Li, Z. S. (2023): Spatio-temporal variation and climatic driving factors of vegetation coverage in the Yellow River Basin from 2001 to 2020 based on kNDVI. – *Forests* 14(3): 620.
- [11] Han, G., Yang, Y. C., Yan, S. Y. (2013): Vegetation activity trend and its relationship with climate change in the Three Gorges area, China. – *Advances in Meteorology* 2013(1): 235378.
- [12] Hu, S., Liu, J., Mao, X. G. (2017): Extraction and change of vegetation coverage of 2007-2010 in northeast China. – *Journal of Northeast Forestry University* 45(7): 45-50.
- [13] Huang, J., Ge, Z. X., Huang, Y. Q., Tang, X. G., Shi, Z., Lai, Y., Song, Z. L., Hao, B. F., Yang, H., Ma, M. G. (2021): Climate change and ecological engineering jointly induced

- vegetation greening in global karst regions from 2001 to 2020. – *Plant and Soil* 475(1): 193-212.
- [14] Jiang, M. C., He, Y. X., Song, C. H., Pan, Y., Tian, S. (2021): Disaggregating climatic and anthropogenic influences on vegetation changes in Beijing–Tianjin–Hebei region of China. – *Science of the Total Environment* 786: 147574.
- [15] Jones, C., Lowe, J., Liddicoat, S., Betts, R. (2009): Committed terrestrial ecosystem changes due to climate change. – *Nature Geoscience* 2(7): 484-487.
- [16] Kou, P., Xu, Q., Jin, Z., Yunus, A. P., Luo, X. B., Liu, M. H. (2021): Complex anthropogenic interaction on vegetation greening in the Chinese Loess Plateau. – *Science of the Total Environment* 778: 146065.
- [17] Law, B. E., Falge, E., Gu, L., Baldocchi, D. D., Bakwin, P., Berbigier, P., Davis, K., Dolman, A. J., Falk, M., Fuentes, J. D., Goldstein, A., Granier, A., Grelle, A., Hollinger, D., Janssens, I. A., Jarvis, P., Jensen, N. O., Katul, G., Mahli, Y., Matteucci, G., Wofsy, S. (2002): Environmental controls over carbon dioxide and water vapor exchange of terrestrial vegetation. – *Agricultural and Forest Meteorology* 113(1-4): 97-120.
- [18] Li, A., Wu, J. G., Huang, J. H. (2012): Distinguishing between human-induced and climate-driven vegetation changes: a critical application of RESTREND in inner Mongolia. – *Landscape Ecology* 27(7): 969-982.
- [19] Li, Z., Sun, Y. H., Zhang, J. C., Zhang, C. (2017): Temporal-spatial analysis of vegetation coverage dynamics in Beijing–Tianjin–Hebei–metropolitan regions. – *Acta Ecologica Sinica* 37(22): 7418-7426.
- [20] Li, Y. H., Teng, J. H., Ma, W. T. (2019): Temporal and spatial evolution characteristics of vegetation coverage in Beijing-Tianjin-Hebei region. – *Bulletin of Surveying and Mapping* 33(11): 1302-1307.
- [21] Li, H., Zhang, H. Y., Li, Q. X., Zhao, J. J., Guo, X. Y., Ying, H., Deng, G. R., Rihan, W., Wang, S. L. (2021): Vegetation productivity dynamics in response to climate change and human activities under different topography and land cover in northeast China. – *Remote Sensing* 13(5): 975.
- [22] Lian, X., Jeong, S., Park, C.-E., Xu, H., Li, L. Z. X., Wang, T., Gentine, P., Peñuelas, J., Piao, S. L. (2022): Biophysical impacts of northern vegetation changes on seasonal warming patterns. – *Nature Communications* 13(1): 1-9.
- [23] Luan, Z. R., Tian, X. H., Lv, F. J., Lu, X. K., Fan, G. L., Li, R. (2022): Analysis of grassland change trend and influencing factors in Zhangjiakou Plateau from 1980 to 2019 based on remote sensing. – *Journal of Hebei GEO University* 45(4): 73-79.
- [24] Ma, Q. M., Long, Y. P., Jia, X. P., Wang, H. B., Li, Y. S. (2019): Vegetation response to climatic variation and human activities on the Ordos Plateau from 2000 to 2016. – *Environmental Earth Sciences* 78: 1-15.
- [25] Mao, P. P., Zhang, J., Li, M., Liu, Y. L., Wang, X., Yan, R. R., Shen, B. B., Zhang, X., Shen, J., Zhu, X. Y., Xu, D. W., Xin, X. P. (2022): Spatial and temporal variations in fractional vegetation cover and its driving factors in the Hulun Lake region. – *Ecological Indicators* 135: 108490.
- [26] Meng, D., Li, X. J., Gong, H. L., Qu, Y. T. (2015): Analysis of spatial-temporal change of NDVI and its climatic driving factors in Beijing–Tianjin–Hebei metropolis circle from 2001 to 2013. – *Journal of Geo-information Science* 17: 1001-1007.
- [27] Nie, T., Dong, G. T., Jiang, X. H., Lei, Y. X. (2021): Spatio-temporal changes and driving forces of vegetation coverage on the loess plateau of Northern Shaanxi. – *Remote Sensing* 13(4): 613.
- [28] Pang, H., Lin, A. P., Holford, M., Enerson, B. E., Lu, B., Lawton, M. P., Floyd, E., Zhao, H. Y. (2006): Pathway analysis using random forests classification and regression. – *Bioinformatics* 22(16): 2028-2036.
- [29] Piao, S. L., Wang, X. H., Park, T., Chen, C., Lian, X., He, Y., Bjerke, J. W., Chen, A. P., Ciais, P., Tømmervik, H., Nemani, R. R., Myneni, R. B. (2019): Characteristics, drivers and feedbacks of global greening. – *Nature Reviews Earth & Environment* 1(1): 14-27.

- [30] Shi, S. Y., Yu, J. J., Wang, F., Wang, P., Zhang, Y. C., Jin, K. (2021): Quantitative contributions of climate change and human activities to vegetation changes over multiple time scales on the Loess Plateau. – *Science of the Total Environment* 755: 142419.
- [31] Sun, Y. L., Guo, P. (2012): Spatio-temporal variation of vegetation coverage index in North China during the period from 1982 to 2006. – *Arid Zone Research* 29(2): 187-193.
- [32] Sun, Q. Q., Liu, C., Chen, T. Y., Zhang, A. B. (2021): A weighted-time-lag method to detect lag vegetation response to climate variation: A case study in Loess Plateau, China, 1982-2013. – *Remote Sensing* 13(5): 923.
- [33] Thenkabail, P. S., Wu, Z. (2012): An automated cropland classification algorithm (ACCA) for Tajikistan by combining Landsat, MODIS, and secondary data. – *Remote Sensing* 4(10): 2890-2918.
- [34] Tian, F., Liu, L. Z., Yang, J. H., Wu, J. J. (2021): Vegetation greening in more than 94% of the Yellow River Basin (YRB) region in China during the 21st century caused jointly by warming and anthropogenic activities. – *Ecological Indicator* 125: 107479.
- [35] Tong, S. Q., Zhang, J. Q., Ha, S., Lai, Q., Ma, Q. Y. (2016): Dynamics of fractional vegetation coverage and its relationship with climate and human activities in Inner Mongolia, China. – *Remote Sensing* 8(9): 776.
- [36] Tucker, C. J., Slayback, D. A., Pinzon, J. E., Los, S. O., Myneni, R. B., Taylor, M. G. (2001): Higher northern latitude normalized difference vegetation index and growing season trends from 1982 to 1999. – *International Journal of Biometeorology* 45(4): 184-190.
- [37] Verma, A. K. (2021): Influence of climate change on balanced ecosystem, biodiversity and sustainable development: An overview. – *International Journal of Biological Innovations* 3(2): 331-337.
- [38] Wang, J., Guo, N., Cai, D. H., Deng, Z. Y. (2009): The effect evaluation of the program of restoring grazing to grasslands in Maqu country. – *Acta Ecologica Sinica* 29(3): 1276-1284.
- [39] Wang, H., Liu, G. H., Li, Z. S., Ye, X., Fu, B. J., Lv, Y. H. (2018): Impacts of drought and human activity on vegetation growth in the grain for green program region, China. – *Chinese Geographical Science* 28: 470-481.
- [40] Xia, M., Jia, K., Zhao, W. W., Liu, S. L., Wei, X. Q., Wang, B. (2021): Spatio-temporal changes of ecological vulnerability across the Qinghai-Tibetan Plateau. – *Ecological Indicators* 123: 107274.
- [41] Xu, K. P., Chi, Y. Y., Wang, J. J., Ge, R. F., Wang, X. H. (2021): Analysis of the spatial characteristics and driving forces determining ecosystem quality of the Beijing-Tianjin-Hebei region. – *Environmental Science and Pollution Research* 28(10): 12555-12565.
- [42] Yan, S. J., Wang, H., Jiao, K. W. (2019): Spatio-temporal dynamics of NDVI in the Beijing-Tianjin-Hebei region based on MODIS data and quantitative attribution. – *Journal of Geo-Information Science* 21: 767-780.
- [43] Yan, K., Gao, S., Chi, H. J., Qi, J. B. (2021): Evaluation of the vegetation-index-based dimidiate pixel model for fractional vegetation cover estimation. – *IEEE Transactions on Geoscience and Remote Sensing* 60: 1-14.
- [44] Yang, W. J., Zhao, Y., Wang, Q. M., Guan, B. L. (2022): Climate, CO₂, and anthropogenic drivers of accelerated vegetation greening in the Haihe river basin. – *Remote Sensing* 14(2): 268.
- [45] Yu, L., Wu, Z. T., Du, Z., Zhang, H., Liu, Y. (2020): Insights on the roles of climate and human activities to vegetation degradation and restoration in Beijing-Tianjin sandstorm source region. – *Ecological Engineering* 159(2): 106105.
- [46] Zhao, Y. B., Sun, R. H., Ni, Z. Y. (2019): Identification of natural and anthropogenic drivers of vegetation change in the Beijing-Tianjin-Hebei megacity region. – *Remote Sensing* 11(10): 1224.
- [47] Zhe, M., Zhang, X. Q., Shen, P. K., Hou, W. J. (2020): Spatial-temporal pattern of temperature variation in Beijing-Tianjin-Hebei region over the period 1957-2017. – *Research of Soil and Water Conservation* 27(5): 194-201.

- [48] Zou, Y., Chen, W., Li, S. L., Wang, T. J., Yu, L., Xu, M., Singh, R. P., Liu, C. Q. (2022): Spatio-temporal changes in vegetation in the last two decades (2001–2020) in the Beijing–Tianjin–Hebei region. – *Remote Sensing* 14(16): 3958.