Spatiotemporal variation of forest land and its driving factors in the agropastoral ecotone of northern China Postprint

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Date: 2022-01-30T22:22:37+00:00

Abstract

As an important natural resource, forest land plays a key role in the maintenance of ecological security. However, variations of forest land in the agropastoral ecotone of northern China (AENC) have attracted little attention. Taking the AENC as an example and based on remote-sensing images from 2000, 2010 to 2020, we explored the spatiotemporal variation of forest land and its driving factors using the land-use transfer matrix, spatial autocorrelation analysis and spatial error model. The results showed that from 2000 to 2020, the total area of forest land in the AENC increased from 75,547.52 to 77,359.96 km2 and the changes were dominated by the transformations among forest land, grassland and cropland, which occurred mainly in areas with the elevation of 500–2000 m and slope of 15°–25°. There was obvious spatial agglomeration of forest land in the AENC from 2000 to 2020, with hot spots of forest land gathered in the southern marginal areas of the Yanshan Mountains and the low mountainous and hilly areas of the Loess Plateau. The sub-hot spots around hot spots moved southward, the sub-cold spots spread to the surrounding areas and the cold spots disappeared. The spatiotemporal variation of forest land resulted from the interactions of natural environment, socioeconomic and policy factors from 2000 to 2020. The variables of average annual precipitation, slope, terrain relief, ecological conversion program and afforestation policy for barren mountains affected the spatial pattern of forest land positively, while those of annual average temperature, slope and road network density influenced it negatively.

Full Text

Preamble

ChinaXiv Cooperative Journal

Spatiotemporal Variation of Forest Land and Its Driving Factors in the Agropastoral Ecotone of Northern China

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Abstract: As an important natural resource, forest land plays a key role in maintaining ecological security. However, variations of forest land in the agropastoral ecotone of northern China (AENC) have attracted little attention. Taking the AENC as an example and based on remote-sensing images from 2000, 2010 to 2020, we explored the spatiotemporal variation of forest land and its driving factors using the land-use transfer matrix, spatial autocorrelation analysis and spatial error model. The results showed that from 2000 to 2020, the total area of forest land in the AENC increased from 75,547.52 to 77,359.96 km^2 and the changes were dominated by the transformations among forest land, grassland and cropland, which occurred mainly in areas with the elevation of 500–2000 m and slope of 15°–25°. There was obvious spatial agglomeration of forest land in the AENC from 2000 to 2020, with hot spots of forest land gathered in the southern marginal areas of the Yanshan Mountains and the low mountainous and hilly areas of the Loess Plateau. The sub-hot spots around hot spots moved southward, the sub-cold spots spread to the surrounding areas and the cold spots disappeared. The spatiotemporal variation of forest land resulted from the interactions of natural environment, socioeconomic and policy factors from 2000 to 2020. The variables of average annual precipitation, slope, terrain relief, ecological conversion program and afforestation policy for barren mountains affected the spatial pattern of forest land positively, while those of annual average temperature, slope and road network density influenced it negatively.

Keywords: forest land; spatiotemporal variation; driving factors; spatial error model; agropastoral ecotone; northern China

Citation: WANG Shiqing, TAO Zefu, SUN Piling, CHEN Sijia, SUN Huiying, LI Nan. 2022. Spatiotemporal variation of forest land and its driving factors in the agropastoral ecotone of northern China. Journal of Arid Land, 14(1): 1–13. https://doi.org/10.1007/s40333-022-0001-4

Introduction

In recent years, rapid urbanization and industrialization in China have dramatically altered land-use patterns, manifested primarily through the rapid expansion of construction land, continuous decrease of natural ecological land, and reconstruction of agricultural production land [?]. Regional land-use changes and their driving factors have consistently been important research topics in land science and global climate change [?]. In particular, comprehensive studies examining how human activities and the natural environment affect land-use change constitute a crucial component of research into the driving mechanisms of land-use changes [?]. The spatiotemporal variation and driving factors of specific land-use types have become important ecological issues [?]. As an important ecological defense line, the AENC is located in an arid and semi-arid transition area where the ecological environment is very sensitive and fragile due to frequent human activities, making it a research hotspot for ecological environmental responses to land-use changes [?].

Forest land is an important natural resource that plays a key role in regional development and ecological security maintenance [?]. Consequently, dynamic monitoring of forest land resources and their driving factors has attracted widespread attention [?, ?]. With the implementation of ecological projects and other socioeconomic measures, land-use types have undergone substantial changes in the AENC, but the effects of these projects on the spatial distribution of forest land and the interaction between socioeconomic development and the natural environment are difficult to measure [?]. Ecological projects such as the Three-North Shelter Forest Program, Grain for Green, and the Taihang Mountain Greening Project have had significant impacts on the evolution of forest land [?], leading directly to large-scale conversion of forest land [?]. Therefore, it is crucial to investigate the factors driving the spatiotemporal variation of forest land in sensitive and fragile areas with extremely important ecological environments.

Currently, research on forest land primarily focuses on dynamic monitoring [?], spatiotemporal patterns and driving factors [?], landscape patterns and gradient effects [?], scenario simulation and prediction [?], transformation and circulation [?, ?], relationships between forest land change and the ecological environment [?, ?], changes in ecosystem service values [?], and management and protection [?, ?]. With advances in remote sensing, geographic information, and big-data mining technology, methods such as landscape pattern metrics, spatial autocorrelation analysis, probit regression models, logistic regression models, and Cellular Automata-Markov Chain models have been widely used in forest land research [?, ?, ?, ?, ?]. However, studies examining the spatiotemporal variation of forest land and its driving factors in the AENC using spatial regression models are currently lacking.

In recent years, rapid economic development in the AENC has exacerbated ecological problems such as vegetation destruction, land degradation, and soil erosion, while conflicts between ecological protection and economic development are becoming increasingly serious. Therefore, for the sake of ecological protection and sustainable development, there is an urgent need to clarify the trend of forest land changes in the AENC. The aims of the present study are to: (1) analyze the transition of forest land in the AENC from 2000 to 2020; (2) reveal the spatiotemporal variation of forest land; and (3) explore the factors driving this spatiotemporal variation.

2.1 Study Area

The AENC includes 226 counties (banners, cities and districts) in the autonomous regions of Inner Mongolia and Ningxia Hui and the provinces of Jilin, Liaoning, Hebei, Shanxi, Shaanxi, Gansu and Qinghai (34°43’ 31’ ‘N-46°57’ 46’ ‘N, 100°57’ 11’ ‘E-125°34’ 11’ ’ E; Fig. 1). The total area of the AENC is 699,078.78 km^2 and its elevation ranges from 160 m below sea level to 4,973 m above sea level. This area is dominated by plateaus, mountains and hills. The AENC has a temperate arid and semi-arid climate, experiencing low temperatures and drought. The annual average temperature is 0°C–8°C, the average annual precipitation is 300–450 mm, and variation of annual precipitation is high, being 15%–30% [?]. With decreasing precipitation from east to west, the vegetation transforms gradually from forest steppe to desert steppe.

2.2 Data Sources and Processing

The data used in this study came from remote-sensing images comprising Landsat images from 2000 to 2010 and Operational Land Image in 2020. These images were obtained from China’ s Geospatial Data Cloud (http://www.gscloud.cn/). Preprocessing of these Landsat images included atmospheric correction in the Environment for Visualizing Images (ENVI) 5.1 and geometric rectification. In total, 281 sample points were collected and classified in August 2020 with Google Earth and spot surveying. Approximately 35% of the sample points were selected randomly for accuracy assessment. The methods of neural-net estimation and man–machine interactive interpretation were used to interpret and classify these images. The results were then tested and verified, with overall accuracies of 87.68%, 89.72% and 88.59% for the images in 2000, 2010 and 2020, respectively, and Kappa coefficients of 0.85, 0.87 and 0.86, respectively, indicating that the interpretation results could meet the needs of this study. Land-use types were divided into six categories: cropland, forest land, grassland, water body, construction land and unused land [?].

The topographical data were derived from a digital elevation model (DEM) with a resolution of 30 m$×$30 m and downloaded from the China Meteorological Science Data Sharing Service Network (http://cdc.cma.gov.cn/). The slope, aspect and terrain relief were extracted from the DEM. The meteorological data downloaded from the same datasets were interpolated spatially by the inverse distance weighting method. The road traffic data (including railways and highways) came from the electronic traffic map (2000 and 2020), and the social and economic statistics such as population and regional gross domestic product came mainly from the statistical yearbooks of these provinces and regions of the

AENC.

We processed the aforementioned data using the ArcGIS 10.4 software, and we used a 10 km$\times$10 km grid as the data carrier and basic analysis unit. Format conversion, mask clipping and vector data rasterization were processed to unify all the spatial data into the Albers projection system. In the same grid, spatial statistics for forest land, meteorology, topography, socioeconomic data and other multisource data were processed, and spatial data for the driving factors of forest land were obtained.

2.3.1 Land-Use Transfer Matrix

The land-use transfer matrix was used to characterize the inter-conversion relationship between forest land and other land types in the AENC from 2000 to 2020. It is expressed as follows [?]:

$$\begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix}$$

where S_{ij} is the area converted from land-use type i to type j (km^2); and n is the number of land-use types.

2.3.2 Spatial Autocorrelation Analysis

The method of spatial autocorrelation analysis is effective for revealing whether the spatial distribution of a spatial element or a property value is related to adjacent regions and the degree of correlation [?]. In the present study, global spatial autocorrelation was used to analyze the spatial distribution characteristics of forest land. Spatial hotspot analysis (Getis-Ord G_i^*) was used to identify the spatial characteristics of forest land clusters in the AENC [?]. The equations were as follows:

Global Moran' s I:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Getis-Ord G_i^*:

$$G_i^* = \frac{\sum_{j=1}^{n} W_{ij} x_j}{\sum_{j=1}^{n} x_j}$$

Standardized $Z(G_i^*)$:

$$Z(G_i^*) = \frac{G_i^* - E(G_i^*)}{\sqrt{var(G_i^*)}}$$

where I is the global Moran' s I; x_i and x_j are the forest land areas of regions i and j, respectively (km^2); $\bar{x}$ is the mean forest land area (km^2); W_{ij} is the spatial weight matrix ($i \neq j$); G_i^* is the statistic of region i; $Z(G_i^*)$ is the standardized value of G_i^*, which is used to execute a Z statistic test for forest land in the AENC; $E(G_i^*)$ is the average of G_i^*; and $var(G_i^*)$ is the coefficient of variation of G_i^*.

The global Moran' s I ranges from -1 to 1. If $I > 0$, the forest land is positively correlated spatially, and the high or low values of forest land are distributed centrally; if $I < 0$, there is a negative correlation, which indicates that forest land from one region is different from those of the surrounding regions; if $I = 0$, forest land occurs randomly. If $Z(G_i^*)$ passes the statistical test and is greater than 0, then region i is surrounded by high values of forest land area and a cluster of high values (a hot spot) forms; if $Z(G_i^*)$ passes the statistical test and is less than 0, then region i is surrounded by low values of forest land area and a cluster of low values (a cold spot) forms.

2.3.3 Explanatory Variables

The spatiotemporal variation of forest land is driven by natural environmental, socioeconomic and regional policy factors [?, ?, ?]. Following previous studies [?, ?, ?], we selected explanatory variables from those three aspects: natural environment, socioeconomic conditions and regional policy factors (Table 1). Natural environment factors play a key role in forest land changes, and six explanatory variables including average annual precipitation, annual average temperature, elevation, slope, aspect and terrain relief were selected to characterize the natural environment features in the AENC. Three explanatory variables of economic density, population density and road network density were selected to reflect the socioeconomic conditions in the AENC. The regional policy is measured by afforestation for barren mountains.

2.3.4 Spatial Regression Model

Generally, the relationship between observed variables and potential driving factors is explored using multiple linear regression [?]. However, as a geographic phenomenon, forest land changes are spatially correlated; therefore, it was necessary to use a spatial regression model that considers the spatial correlation among regions to identify the driving factors of forest land changes. The spatial regression model includes a spatial lag model (SLM) and a spatial error model (SEM) [?, ?] that were used to analyze the relationship between the spatiotemporal variation of forest land and the explanatory variables. Using the ArcGIS and GeoDa software, we screened the appropriate spatial measurement model by using the Lagrange multiplier (LM) test and by checking the spatial autocorrelation of forest land distribution.

The SLM is expressed as follows [?]:

$$Y = \rho WY + X\beta + \varepsilon$$

The SEM is expressed as follows [?]:

$$Y = X\beta + \lambda W\varepsilon + \mu$$

where Y is the forest land area of spatial regional unit (km^2); W and ρ are the spatial adjacency weight and its estimated coefficient, respectively; β is the coefficient of explanatory variable; X is the explanatory variable matrix; ε is a random error; λ is the coefficient of regression; and μ is an independent random error.

3.1 Transition of Forest Land in the AENC

From 2000 to 2020, the total area of forest land increased from 75,547.52 to 77,359.96 km^2 with a 2.40% increase rate per year. The newly increased forest land was scattered mainly in the mountainous areas of northern Hebei Province and the low mountainous and hilly areas of the Loess Plateau (Fig. 2). As shown in Figure 3, the total area of forest land decreased by 111.55 km^2 in the AENC from 2000 to 2010. On the one hand, the decreased forest land was converted mainly to grassland and cropland. The areas of this conversion for grassland and cropland were 9,142.64 and 517.99 km^2, accounting for 94.19% and 5.34% of the total area changed, respectively. The conversion of forest land to grassland occurred mainly in the mountainous areas of northern Hebei Province and the Inner Mongolia Autonomous Region. Furthermore, the conversion of forest land to cropland was distributed mainly in river valleys and intermountain basins in the counties of Hunyuan, Lingqiu and Guangling with low elevation and flat terrain.

On the other hand, increased forest land was derived mainly from grassland and cropland. The areas of conversion were 8,613.02 and 852.37 km^2 for grassland and cropland, accounting for 89.76% and 8.78% of the total area changed, respectively. The conversion of grassland to forest land occurred mainly in the mountainous areas of northern Hebei Province, while the conversion of cropland to forest land was scattered in areas of high elevation and complex terrain, including the counties of Gujiao, Jingle, Chongli and Zhangbei. In recent years, with the implementation of ecological projects, the expansion of forest land was derived mainly from grassland and cropland from 2010 to 2020, which accounted for 1,923.99 and 2,991.23 km^2, respectively. Cropland was converted to forest land because of the construction of farmland shelterbelts, and the increase of forest land improved the ecological environment further.

The topographical gradient effect of forest land was obvious in the AENC (Fig. 4). Forest land changes were distributed mainly in areas with elevations of 500–2000 m and slopes of 15°–25°. With the implementation of ecological projects such as the Three-North Shelter Forest Program, Grain for Green and the Taihang Mountain Greening Project, forest land expanded into regions with a higher topographic gradient in the AENC, which occupied a dominant position at elevations exceeding 2000 m and slopes exceeding 15°.

3.2.1 Distribution Trend of Forest Land

The geostatistical analysis module of ArcGIS 10.4 software was used to analyze the distribution trend of forest land in the AENC from 2000, 2010 to 2020 (Fig. 5). The change in forest land in the AENC was very obvious. The overall spatial pattern of forest land showed an inverted U-shaped differentiation trend in the east-west direction, being high in the north and low in the south from 2000 to 2020.

3.2.2 Spatiotemporal Variation of Forest Land

The global Moran' s I of forest land in the AENC from 2000 to 2020 was calculated using ArcGIS 10.4 (Table 2) and ranged from 0.323 to 0.328 from 2000 to 2020. The $Z(G_i^*)$ values were positive and all tested significantly at the 0.01 level, which indicated a positive spatial autocorrelation of forest land. This result showed that areas with similar levels of forest land tended to be spatially agglomerated. Furthermore, the global Moran' s I maintained a downward trend in its fluctuations, indicating that the degree of agglomeration continued to weaken after a minor intensification in the AENC from 2000 to 2020.

To effectively analyze the spatiotemporal variation of forest land in the AENC, we divided the values of Getis-Ord G_i^* from high to low into five types—hot spot, sub-hot spot, sub-cold spot, cold spot and non-significant area—using the Jenks natural-breaks method [**?**]. The spatial pattern of forest land showed an obvious spatial difference in the AENC from 2000 to 2020 (Fig. 6). The spatial pattern of hot spots evolved significantly in the AENC, which was manifested mainly as a reduction trend from 2000 to 2020. Forest land was distributed mainly in mountainous areas with higher elevations and slopes. From 2000 to 2020, the number of counties (districts) in hot spots decreased constantly, becoming gathered in the southern marginal area. Two clusters of high forest land area formed in 23 counties (districts) located in the Yanshan Mountains and the low mountainous and hilly areas of the Loess Plateau.

During this time, the spatial pattern evolution of sub-hot spots moved southward, which occurred mainly in regions around the hot spots. With the implementation of ecological projects, in 2020, the sub-hot spots covered 13 counties (districts) located in the Yanshan Mountains and the Loess Plateau, where the ecological environment is very sensitive and fragile. Meanwhile, the sub-cold spots spread to the surrounding areas, and the number of counties (districts) with sub-cold spots increased from 43 to 47 from 2000 to 2020. These counties (districts) were distributed mainly in areas with low elevation and flat terrain, such as the valleys of Huangshui, the Yellow River and the Daqing River, located in the provinces of Qinghai, Gansu and Inner Mongolia Autonomous Region, where two clusters of low forest land area (sub-cold spots) formed. Moreover, the spatial pattern of cold spots changed significantly. In 2000, there was a cluster of low forest land area (cold spot) in the region between the provinces of Qinghai and Gansu, including the county of Minhe in Qinghai and the district of Qilihe in Gansu; however, this cold spot disappeared as Minhe and Qilihe fell into sub-cold spots in 2020 (Fig. 6c).

3.3 Driving Factors of Spatiotemporal Variation of Forest Land

In this study, the LM test was used to select the spatial measurement model. Conventional least-squares analysis showed that the results of SEM and robust LM for the years 2000 and 2020 both passed the test at the 0.01 level. This result indicated that SEM was suitable for identifying the factors driving the spatiotemporal variation of forest land in the AENC. The spatial variation was influenced by natural environment, socioeconomic and regional policy factors (Table 3).

3.3.1 Natural Environment Factors

As shown in Table 3, the significant variables are average annual precipitation, annual average temperature, slope, aspect and terrain relief. This result indicates that climate and topographic conditions basically determined the spatial pattern of forest land in the AENC. Precipitation and temperature are important natural conditions for land use, determining the level of climate-induced potential productivity in a region. The spatiotemporal variation of forest land was affected significantly by precipitation and temperature in the AENC from 2000 to 2020. There was a positive correlation between the average annual precipitation and the distribution of forest land, which passed the significance test at the 0.01 level in 2000 and 2020, while it was negatively correlated with annual average temperature. The AENC is located in arid and semi-arid areas, where the distribution of vegetation cover is consistent with precipitation. Therefore, the higher the precipitation, the better the forest land cover.

In mountainous areas, sunny slopes and flat areas are often suitable for agricultural production, so cropland and garden land usually occupy the dominant position there, while forest land is scarce. The regional differentiation of land resources is restricted by topographical conditions, which can affect the redistribution of heat and water. The distribution of forest land was correlated positively with slope and terrain relief but negatively with aspect. In the southern and northwestern mountainous areas, there was a wide distribution of forest land. As shown in Figure 5, the hot spots of forest land covered the mountainous areas in northern Hebei Province and the low mountainous and hilly areas of the Loess Plateau, with larger slopes and complex terrain. Slope was found to be significantly and positively associated with forest land area ($P < 0.01$), and the coefficients were 2,169.820 and 3,901.600 in 2000 and 2020, respectively. Terrain relief was not significant in 2000 but was highly significant ($P < 0.01$) and positively associated with forest land area in 2020, with a coefficient of 138.368.

3.3.2 Socioeconomic Factors

With improved socioeconomic levels, the distribution pattern of forest land changed significantly. Table 3 shows that two variables passed the significance test of SEM in the socioeconomic dimension: (1) population density was significantly and negatively associated with the dependent variable ($P < 0.05$) in 2000 with a coefficient of -0.022, but it became insignificant in 2020; and (2) road network density was highly significant ($P < 0.01$) in 2000 and 2020 and was also negatively correlated with the distribution of forest land, with coefficients of -0.711 and -2.856, respectively. These results showed that forest land had a lower probability of appearing in regions with intensive population, more-developed economy and superior transportation location, where cropland and construction land were dominant. Forest land was distributed mainly in suburbs and remote areas with inconvenient transportation.

3.3.3 Regional Policy Factors

Table 3 shows that two variables impacted the distribution of forest land in the aspect of regional policies: forest land area was significantly and positively correlated with ecological projects and afforestation policy for barren mountains. The former was significantly relevant to forest land ($P < 0.01$) in 2020, with a regression coefficient of 9,643.830. Implemented in 1999 and restarted in 2014, the Grain for Green project resulted in dramatic changes in forest land distribution in the AENC. Moreover, afforestation policy for barren mountains was significantly and positively relevant to forest land ($P < 0.01$ in 2000 and $P < 0.05$ in 2020, respectively), with coefficients of 311.692 and 2,298.230, respectively. With the implementation of ecological projects, the evolution of forest land has had significant impacts. These results indicate that the probability of forest land increased in regions located in ecological construction areas from 2000 to 2020.

4.1 Effects of Natural Environment Factors on Forest Land in the AENC

According to the results of the spatial regression model (Table 3), natural environment factors such as average annual precipitation, annual average temperature, slope, aspect and terrain relief were the key driving factors for the spatial distribution of forest land, which were consistent with existing research. For example, Morales et al. [?] and Kibler et al. [?] found that precipitation was an important natural factor affecting the spatial pattern of forest land. Fu et al. [?] and Deng et al. [?] pointed out that climatic and topographical factors, such as annual average temperature, altitude and slope, had important impacts on the spatial distribution of forest land. Compared with previous studies, the influence of natural environment factors such as average annual precipitation, annual average temperature, slope, aspect and terrain relief on the spatial distribution of forest land was positive. The AENC, located in the transitional zone from farming areas to pastoral areas and from semi-arid areas to arid areas, is an important ecological security barrier and water conservation area of Beijing-Tianjin-Hebei with a sensitive ecological environment. Those natural environment factors represented the regional natural conditions, which reflected the macro-geographic background of the AENC to a certain extent. Therefore, the effects of those natural environment factors on the spatial distribution of forest land in the AENC were synthetic. Similar results were reported by Chen et al. [?] and Wang et al. [?], who found that spatial differentiation of forest land resulted from altitude, aspect and slope position. Since the 21st century, the government has implemented ecological projects in the AENC, which resulted in the expansion of forest land in high altitude and slope areas. Moreover, because the AENC was located in transitional areas from monsoon to non-monsoon regions, its sunny slopes and semi-sunny slopes were also windward slopes, where heat and precipitation were relatively abundant. Development of forest land in these areas was more suitable. Similar results were confirmed by Nirmal et al. [?] and Wang et al. [?], who found that geographical location influenced drought distribution and the growth of shrub.

4.2 Effects of Human Activities on Forest Land in the AENC

Socioeconomic and policy factors played important roles in the spatial distribution of forest land. Our results found that road network density had a negative impact on the spatial distribution of forest land in the AENC, and the impact of population density gradually weakened. Yu et al. [?] and Bochet et al. [?] also found that population growth and economic development had significant impacts on the transition and spatial distribution of forest land through qualitative analysis. Rapid economic development, improvement of urbanization level, changes of industrial structure and urban population growth usually resulted in the decrease of forest land [?, ?, ?]. Due to limited socioeconomic construction and slow development of industry and agriculture in the AENC, the impact of economic density on the spatial distribution of forest land weakened. Moreover, population outflow was serious and the residents were gradually decreasing in the AENC. The influence of population density on the spatial distribution of forest land is also decreasing. With the implementation of new urbanization construction and rural revitalization strategy in the AENC, traffic facilities had been continuously improved, and road accessibility had gradually increased, which caused changes in the spatial distribution pattern of forest land.

Policy factors, especially the Grain for Green project, had significant effects on the spatiotemporal variation of forest land in the AENC. Deng et al. [?] and Liu et al. [?] found that the Grain for Green project was an important driving factor for the increase of forest land in mountainous areas, which was consistent with this study. Compared with previous studies, the impact of ecological projects and afforestation policy for barren mountains on the spatial distribution of forest land in the AENC had gradually enhanced. Owing to a series of ecological projects that have been carried out since 1999, the function of the ecological security barrier of the AENC had been enhanced.

5 Conclusions

This study found that the changes in forest land in the AENC from 2000 to 2020 were dominated by conversion among forest land, grassland and cropland, which occurred mainly in areas with elevations of 500–2000 m and slopes of 5°–25°. The spatial pattern of forest land from 2000 to 2020 showed a trend of inverted U-shaped differentiation in the east–west direction, being high in the north and low in the south. The hot spots of forest land gathered in the southern marginal areas of the Yanshan Mountains and the low mountainous and hilly areas of the Loess Plateau, and the sub-hot spots around the hot spots moved southward. The sub-cold spots spread to the surrounding areas, and the cold spots disappeared. Spatiotemporal variation of forest land was influenced by natural environment, socioeconomic and policy factors. Impacts of terrain relief and ecological conversion policy increased, while those of population density decreased. Consequently, this study offers scientific references for protection of forest land and ecological construction in the AENC. However, further study should be conducted to explore the impact of intensity of policy implementation and other policy factors that will influence the distribution of forest land.

Acknowledgements

This research was funded by the National Natural Science Foundation of China (41971238), the Ministry of Education Humanities and Social Youth Foundation of China (19YJCZH144), the Natural Science Foundation of Shandong Province, China (ZR2019QD006), and the National College Student Innovation Training Project (S202010446004).

References

Bochet E, Molina M J, Monleon V, et al. 2021. Interactions of past human disturbance and aridity trigger abrupt shifts in the functional state of Mediterranean holm oak woodlands. CATENA, 206: doi: 10.1016/J.CATENA.2021.105514.

Cao R F, Zhang A L, Cai Y Y. 2014. Economic compensation partition for cultivated land protection and fiscal transfer payment: Take Hubei Province as example. China Population, Resources and Environment, 24(12):14–22. (in Chinese)

Cao Y G, Yao L J, Hao Y, et al. 2008. Research on regional forestry pattern, driving force and ecological value. Research of Soil and Water Conservation, 15 (2): 73–79. (in Chinese)

Chen Y, Lin Y W, Lin L L, et al. 2017. Study on land use change in Putian City and spatial simulation of forestland transition based on Markov model and

Logistic regression model. Journal of China Agricultural University, 22(2): 87–97. (in Chinese)

Chen Y Q, Yang P. 2001. Recent progresses of international study on land use and land cover change. Economic Geography, 21(1): 95–100. (in Chinese)

Clarke P J. 2003. Composition of grazed and cleared temperate grassy woodlands in eastern Australia: patterns in space and inferences in time. Journal of Vegetation Science, 14(1): 5–14.

Dahal N M, Xiong D H, Neupane N, et al. 2021. Spatiotemporal analysis of drought variability based on the standardized precipitation evapotranspiration index in the Koshi River Basin, Nepal. Journal of Arid Land, 13(5): 433–454.

Deng Y J, Hou M Y, Zhang X, et al. 2021. Analysis of driving forces of forest land change in Qinba Mountain area of Shaanxi based on the Logistic regression model. Journal of Nanjing Forestry University (Natural Sciences Edition), 45(6): 90–98. (in Chinese)

Du G M, Sun X B, Liu Y S. 2016. Analysis of ecological restoration on ecosystem service and its human driving factors in Yan'an City. Research of Soil and Water Conservation, 23(3): 233–239. (in Chinese)

Dwomoh F K, Brown J F, Tollerud H J, et al. 2021. Hotter drought escalates tree cover declines in blue oak woodlands of California. Frontiers in Climate, doi: 10.3389/FCLIM.2021.689945.

Feng Y, Tang X, Bao Q F. 2021. Driving factors of forest ecological security in Yangtze River Delta based on GWR Model. Ecological Economy. [2021-03-21]. https://kns.cnki.net/kcms/detail/53.1193.F.20211003.1204.004.html. (in Chinese)

Fu J X, Cao G C, Guo W J. 2021. Terrain gradient change of land use and its geographical detector of terrain factors on the south-facing slope of Qilianshan Mountains from 1980 to 2018. Research of Soil and Water Conservation, 28(6): 371–381. (in Chinese)

Garner G, Malcolm L A, Sadler J P, et al. 2015. Inter-annual variability in the effects of riparian woodland on micro-climate, energy exchanges and water temperature of an upland Scottish stream. Hydrological Processes, 29(6): 1080–1095.

Godlee J L, Ryan C M, Bauman B, et al. 2021. Structural diversity and tree density drives variation in the biodiversity-ecosystem function relationship of woodlands and savannas. New Phytologist, 232(2): 579–594.

Gou M M, Liu C F, Li L, et al. 2021. Ecosystem service value effects of the Three Gorges Reservoir Area land transformation under the perspective of "production-living-ecological" space. Chinese Journal of Applied Ecology, 32(11): 3933–3941. (in Chinese)

Hou W, Hou X Y, Sun M, et al. 2021. Land use/land cover change along low-middle latitude coastal areas of Eurasia and their driving forces from 2000 to 2010. World Regional Studies, 30(4): 813-825. (in Chinese)

Kibler C L, Schmidt E C, Roberts D A, et al. 2021. A brown wave of riparian woodland mortality following groundwater declines during the 2012-2019 California drought. Environmental Research Letters, 16(8): 084030, doi: 10.1088/1748-9326/AC1377.

Li J, Wang X, Chang S L, et al. 2021. Distribution characteristics and influencing factors of mercury on the soil profile of Picea Schrenkiana forest. Environmental Chemistry, 40(6): 1723-1732. (in Chinese)

Li Y, Xiao L M, Hu W M, et al. 2021. Spatio-temporal pattern of land use change in Changsha-Zhuhou-Xiangtan core areas and its driving forces. Economic Geography, 41(7): 173-182. (in Chinese)

Li Y, Zhao Z B, Wang L Z, et al. 2021. Vegetation changes in response to climatic factors and human activities in Jilin Province, China, 2000-2019. Sustainability, 13(16): 8956.

Liu C, Huo Y W, Xu Y Q, et al. 2018. Changes in cultivated land and influencing factors before and after the implementation of Grain for Green Project in Zhangjiakou City. Journal of Natural Resources, 33(10): 1806-1820. (in Chinese)

Liu J X, Gao J X. 2008. Changes of land use and landscape pattern in the boundary change areas in farming-pastoral ecotone of Northern China. Transactions of the Chinese Society of Agricultural Engineering, 24(11): 76-82. (in Chinese)

Liu J Y, Zhang Z X, Kuang W H, et al. 2010. Spatial patterns and driving forces of land use change in China during the early 21st century. Journal of Geographical Sciences, 20(4): 483-494.

Liu J Y, Kuang W H, Zhang Z X, et al. 2014. Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s. Journal of Geographical Sciences, 69(1): 3-14.

Liu M, Zhao C W, Shi M H. 2012. Spatial autocorrelation analysis of multi-scale land use change at mountainous areas in Guizhou Province. Transactions of the Chinese Society of Agricultural Engineering, 28(10): 239-246. (in Chinese)

Liu M Z, Wang Y F, Pei H W. 2021. The changes of land use and carbon storage in the northern farming-pastoral ecotone under the background of returning farmland to forest (grass). Journal of Desert Research, 41(1): 174-182. (in Chinese)

Luo Z W, Li Y H, Hu X J, et al. 2021. Analysis of forest landscape pattern evolution and its influencing factors in Hunan Province. Research of Soil and Water Conservation, doi: 10.13869/j.cnki.rswc.20210820.002. (in Chinese)

Morales M C, Steffen M, Samartin S, et al. 2020. Long-term responses of Mediterranean mountain forests to climate change, fire and human activities in the Northern Apennines (Italy). Ecosystems, 24: 1361-1377.

Njoghomi E E, Valkonen S, Kaelsson K, et al. 2021. Regeneration dynamics and structural changes in Miombo woodland stands at Kitulangalo Forest Reserve in Tanzania. Journal of Sustainable Forestry, 40(6): 539-557.

Peng J, Du Y Y, Liu Y X, et al. 2017. From natural regionalization, land change to landscape service: The development of integrated physical geography in China. Geographical Research, 36(10): 1819-1833. (in Chinese)

Qing F, Chen P X, Yang B G, et al. 2020. Kernel density hot spot detection and spatial autocorrelation analysis of accessible facility spatial layout: a case study of outdoor public space in central of Beijing. Bulletin of Surveying and Mapping, (9): 140-142. (in Chinese)

Ren P, Wu T, Zhou J M, et al. 2016. Analysis of spatial distribution pattern and evolutionary characteristics of cultivated lands based on spatial autocorrelation model and GIS platform: A case study of Longquanyi District, Chengdu, China. Chinese Journal of Eco-Agriculture, 24(3): 325-334. (in Chinese)

Rohde M M, Stella J C, Roberts D A, et al. 2021. Groundwater dependence of riparian woodlands and the disrupting effect of anthropogenically altered streamflow. Proceeding of the National Academy of Science of the United States of America, 118(25): e2026453118, doi: 10.1073/PNAS.2026453118.

Shao Y K, Zhu C M, Xu X L, et al. 2019. Analysis of spatial and temporal changes and attribution discrimination of forestland in Anhui Province from 2000 to 2015. Ecological Science, 38(6):15-21. (in Chinese)

Shriver R K, Yackulic C B, Bell D M, et al. 2021. Quantifying the demographic vulnerabilities of dry woodlands to climate and competition using range wide monitoring data. Ecology, 102(8): e03425, doi: 10.1002/ECY.3425.

Sun S L, Zhang X P. 2021. Analysis on the spatiotemporal evolution of land use transformation and its ecological environment effect in Shaanxi Province. Research of Soil and Water Conservation, 28(6): 1-9. (in Chinese)

Wan A G, Wang J Q, Wu K Q. 2019. Temporal and spatial characteristics and driving factors of forest land change in Jiangxi. Anhui Agricultural Science Bulletin, 47(7): 128-131. (in Chinese)

Wang C, Ouyang H, Maclaren V, et al. 2007. Evaluation of the economic and environmental impact of converting cropland to forest: A case study in Dunhua County, China. Journal of Environmental Management, 85(3): 746-756.

Wang J Y, Liu Y S. 2009. Land use and cover change and its driving forces in Sanya. Journal of Natural Resources, 24(8): 1458-1466. (in Chinese)

Wang R, Tang C W, Li Z, 2021. Ecological suitability evaluation based on GIS-a case study of Yiwagou forest area, Diebu, eastern Qinghai-Tibet Plateau.

Academic Research, 4(3): 3–10.

Wang Z T, Yang L, Li G, et al. 2021. Distribution and diversity of herbage under Caragana korshinskii plantation at hillslope scale in the semi-arid loess hilly region. Journal of Desert Research, 41(2):120–128. (in Chinese)

Wei C P. 2020. Problems and countermeasures in the protection and management of forest land resources in state-owned forest farm: A case study of Huangmian forest farm directly under Guangxi Zhuang Autonomous Region. Anhui Agricultural Science Bulletin, 26(8): 53–54. (in Chinese)

Xi M Z, Zhao Z Q, Wu P S, et al. 2021. Changes and predictions of land use in mountain section of the Hutuo River Basin based on improved CA-Markov model. Journal of Northwest Forestry University, 36(4): 150–158. (in Chinese)

Xie M, Gong Z W. 2019. Forest resource monitoring and driving force analysis based on high-resolution satellite images. Journal of Central South University of Forestry & Technology, 29(5): 30–36. (in Chinese)

Yang L, Fu C. 2018. Spatio-temporal simulation of Gannan ecological barrier under different scenarios. Scientia Geographica Sinica, 38(3): 457–463. (in Chinese)

Yu H, Zhang B, Wang Z M, et al. 2017. Land cover change and its driving forces in the republic of Korea since the 1990s. Scientia Geographica Sinica, 37(11): 1755–1763. (in Chinese)

Yu Y, Cheng Q W, Yu W F, et al. 2020. Study on impact of rural-household differentiation on forest land circulation behavior. Forestry Economics, 42(8): 23–31. (in Chinese)

Zhang Y, Yang B G, Wang M, et al. 2020. Study on the spatial changes and driving forces of forest land in Beijing-Tianjin-Hebei Region. Science of Surveying and Mapping, 45(9): 104–110. (in Chinese)

Zhou C Q, Liu S Y, Wang P. 2018. Analysis of the driving factors of land use and change based on GIS-Logistic coupling model in Guanghe County. Journal of Gansu Agriculture University, 53(3): 118–125. (in Chinese)

Zhou D C, Zhao S Q, Zhu C. 2012. The impact of the Grain for Green Project on the land use/cover change in the northern farming-pastoral ecotone, China-a case study of Kezuohouqi County. Scientia Geographica Sinica, 32(4): 442–449. (in Chinese)

Zhu L. 2015. Analysis of the relationship between forest land change and ecological environment coupling in Doron County in the past 20 years. Inner Mongolia Forestry, (8): 10–11. (in Chinese)

Note: Figure translations are in progress. See original paper for figures.