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Analysis of the environmental Kuznets curve for forest fragmentation: The case of Beijing-Tianjin-Hebei region in China

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ABSTRACT

In recent decades, the international community has become increasingly concerned about several important environmental challenges including forest fragmentation. In this study, we develop a county-level panel dataset for the Beijing-Tianjin-Hebei (BTH) region of China from 2000 to 2018 and use remote-sensing image data to estimate forest fragmentation. We use a panel threshold regression model to group sample counties and examine the link between forest fragmentation and economic growth at various economic development levels in the BTH region based on the environmental Kuznets Curve (EKC) theory. A robustness test was performed to confirm the validity of the findings. In the sample counties with various levels of economic development, we found different relationships between forest fragmentation and per capita GDP. Inverted "N" and "N" shapes represent the EKC of forest fragmentation in the low- and high-income groups, respectively, and most data show that forest fragmentation reduces with economic growth. Policy changes to reduce forest fragmentation are recommended to promote coordinated and environmentally friendly development in the BTH region.

1. Introduction

The conservation of forested landscapes and economic development are currently in conflict due to urbanization and industrialization in emerging countries (Zhang et al., 2013). Forest fragmentation refers to the process by which integrated forests are divided into smaller independent patches because of deforestation or other land-type changes (Lord and Norton, 1990; Riitters et al., 2004). Anthropogenic and natural disturbances have caused profound changes in the forest landscapes on Earth (Li et al., 2008) and accelerated the process of global forest fragmentation (Zhang et al., 2013). Forest fragmentation can undermine forest quality, weaken ecosystem services, decrease biodiversity, increase the risk of invasive species, reduce ecosystem quality, and even alter climatic conditions (Noah and Puneet, 2021; Di Giulio et al., 2009; Ma et al., 2017; Liu et al., 2019; Yu et al., 2020; Li et al., 2021).

According to the 7th China Forest Resources Inventory data from 2003 to 2008, >30.27% of China's forests have a continuous distribution area of <10 ha. In the agricultural and desertified areas in the northeastern counties, the woods are mainly strip forests. In the central and eastern regions' agricultural areas, and desertified areas of the northwestern region, the proportion of forest area exceeds 90% of the grid unit (1 km × 1 km), accounting for <15% (Long et al., 2018). In the southern collective forest region, the fragmentation of forestland management units has exacerbated the forest fragmentation problem (Li et al., 2011). This trend makes it difficult to satisfy society's growing ecological needs and poses serious challenges to forest carbon sequestration and global carbon neutrality commitments.

The forest fragmentation analysis in our study was tailored to the Beijing-Tianjin-Hebei (BTH) region of China, one of China's most vibrant economic growth regions. China's capital, Beijing, and its surrounding areas are considered China's "capital economic circle," and the BTH region has always played a pivotal role in the country's overall development strategy and economic pattern (Xu et al., 2021). However, in the process of regional development, a series of ecological and environmental problems have emerged in the BTH region (Chi et al., 2015), which lacks large-scale ecological forests and where the problem of forest fragmentation is prominent (Wang et al., 2018). Forest fragmentation is hypothesized to be related to economic development; thus,

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understanding the relationship between economic development and forest fragmentation in the BTH region is necessary to improve forest ecology and ensure sustainable economic growth (Hou et al., 2020).

However, there is a lack of research on the relationship between forest fragmentation and economic development, with previous studies focusing largely on that of forested areas. An important theoretical basis for studying the relationship between economic development and environmental conservation is the environmental Kuznets Curve (EKC) hypothesis, which is an empirical model that describes the nonlinear relationship between environmental quality and economic growth. Forest fragmentation is a more complex process than changes in forest cover. Considering the possible nonlinear relationship between economic development and forest fragmentation, the EKC framework was selected as the theoretical basis for this analysis.

An important assumption underlying the EKC hypothesis is the homogeneity assumption, which disregards regional differences in economic development and other aspects. To satisfy the homogeneity assumption of economic development, we selected economic development level as the threshold variable for county grouping and identified the threshold value using a panel threshold regression model. The sample counties in the BTH region were grouped according to their threshold values, and forest fragmentation was measured using remote-sensing images. Drawing on the EKC framework, we used the panel data model to verify the EKC relationship between forest fragmentation and per capita GDP in different groups, and analyzed the differences or convergences of EKC characteristics in different groups using the 2000–2018 county-level panel dataset. Finally, a robustness test was conducted to ensure the reliability of the estimated results.

This study makes the following contributions. First, compared with exogenous grouping, we take advantage of the threshold regression model to automatically identify the endogenous characteristics of the data and reasonably divide the samples, overcoming the randomness and subjectivity of traditional grouping methods. Second, based on the interdisciplinary perspective of human geography and forestry economics, we improve the accuracy of the research conclusions using county-level data and econometric regression models, providing practical guidance for promoting the coordinated development of economic growth and forest ecology. Finally, this study helps illuminate the complex mechanism by which economic development influences forest fragmentation, expanding the reach of EKC research, and contributing new evidence from China to this important research field.

2. Literature review

Most research analyzes the meaning of forest fragmentation from the perspective of forestland use or landscape ecology. From the perspective of forestland use, forest fragmentation is the process by which previously large, continuous forests are transformed into smaller, isolated fragments. This process gradually transforms the forest from a single, homogeneous, and integrated whole into a complex, heterogeneous, and discontinuous mosaic of smaller forests (Lord and Norton, 1990; D'Eon et al., 2002; Di Giulio et al., 2009; Li et al., 2010). From the perspective of landscape ecology, forest fragmentation is mainly characterized by an increase in the number of patches and a decrease in the average patch area. The patch shape tends to be irregular, habitat area shrinks, and forest patches are isolated from each other, forming forest islands (Lele et al., 2008; Li et al., 2011).

Studies on forest fragmentation have focused on its characteristics and spatiotemporal evolution (Rivas et al., 2021; Yang et al., 2018; Ning et al., 2015; Moreno-Sanchez et al., 2011; Harper et al., 2007), driving factors (Paul and Banerjee, 2021; Mandal and Chatterjee, 2021; Li et al., 2021; Das et al., 2017; Li et al., 2008), and their impacts (Gestich et al., 2022; Cordeiro and Howe, 2003; Lynch and Whigham, 1984). Although forest fragmentation is a nuanced discussion, the literature on deforestation and forest transition could contribute to understanding the factors that drive or reverse forest fragmentation.

Some studies have argued that human activities and disturbances significantly alter forest ecosystems (Lambin and Meyfroidt, 2010). Population pressure is an important driving factor of forest fragmentation (Lele et al., 2008; Tang et al., 2012). Population growth increases the demand for agricultural products and prompts forest managers to change land-use patterns, leading to forest fragmentation (Mahapatra and Kant, 2005; Bhattarai and Hammig, 2001; Abdullah and Nakagoshi, 2006). High population density and high demand for forest products have intensified the use of natural resources, such as forests. Agricultural intensification is another important factor affecting forests. Agricultural intensification prompts people to abandon marginal farmlands, which can alleviate the pressure on forest resource utilization caused by population pressure and help reduce forest fragmentation (Gingrich et al., 2021; Li and Liu, 2015; Lorenzen et al., 2020). Moreover, rural areas have historically relied on fuelwood for cooking and heating, and the overharvesting of fuelwood has been identified as a key factor leading to forest degradation (Pelletier et al., 2021). The transition from traditional household energy consumption (e.g., fuelwood) to modern energy consumption (e.g., electricity) has greatly reduced fuelwood consumption, positively impacting forest restoration and fragmentation (Gingrich et al., 2021; Mazzone et al., 2021). In addition, studies have shown that logging activities typically increase forest fragmentation (Etter et al., 2005; Miyamoto et al., 2014; Hermosilla et al., 2019). The implementation of key forestry projects in China, such as the sloping land conversion program in the BTH region, has played a positive role in promoting forest transition and improving forest ecological function (Viña et al., 2016; Pei et al., 2019; Zhou et al., 2019).

Despite these studies, few have explored the relationship between forest fragmentation and economic development. The EKC hypothesis provides an important analytical framework for studying this relationship. After the EKC hypothesis was proposed, scholars empirically tested it from different perspectives, regions, and industries. The research findings on the EKC hypothesis can be divided into the following four categories: ① The shape of the EKC is "U" or inverted "U" (Grossman and Krueger, 1991; Selden and Song, 1994; Galeotti et al., 2006a, 2006b; Motel et al., 2009; Zhu et al., 2010; Liu et al., 2016; Li et al., 2017; Andrée et al., 2019; Caravaggio, 2020; Ajanaku and Collins, 2021); ② The shape of the EKC is "N" or inverted "N" (Galeotti et al., 2006a, 2006b; Kang et al., 2016; Kijima et al., 2010; Pandit and Paudel, 2016; Sarkodie and Strezov, 2019; Sinha and Bhattacharya, 2017; Friedl and Getzner, 2003; Han and Lu, 2008); ③ the EKC is a linear change (Richmond and Kaufmann, 2006; Wagner, 2008; Shafik, 1994; Zheng and Liu, 2011); and ④ the EKC hypothesis is not supported (Agras and Chapman, 1999; He and Richard, 2010; Leblois et al., 2017; Cary and Bekun, 2021).

Some studies have explored the EKC relationship between forest resource conservation and economic development. Ahmed et al. (2015) explored the EKC hypothesis in Pakistan using time-series data from 1980 to 2013, using deforestation as an indicator of environmental degradation. The results showed that the negative impact of economic growth on deforestation in Pakistan was decreasing, confirming the EKC hypothesis. Caravaggio (2020) verified the inverse U-type EKC relationship of deforestation based on 55-year periodic forest inventory panel data from 114 countries. Zhu et al. (2022) selected forest loss rate as the explained variable and concluded that the forest loss rate in China monotonically decreased with economic growth, and that there were clear differences in forest loss rate changes with economic growth in different regions. Chen and Wang (2013) selected urban green coverage rate as the explained variable and concluded that an N-shaped EKC exists between urban green spaces and economic development in China. Hou et al. (2020) and Hou and Yao (2019a, 2019b) used forest density and forest stock per capita as indicators of forest quality, concluding that the relationship between China's forest quality and economic growth was U-shaped and inverted N-shaped, respectively, with significant regional differences. Zambrano-Monserrate et al. (2018) confirmed a U-shaped deforestation EKC relationship in France, Germany, Greece, Portugal, and Türkiye from 1974 to 2013. Using data from 52 developing countries from 1972 to 2003, Chiu (2012) verified the existence of an inverted U-shaped EKC between deforestation and real income, and the empirical results indicated a strong threshold effect between deforestation and real income. Thus, it is evident that forest EKC test results vary with study areas, samples, and forest resource index selections.

An important assumption of the EKC hypothesis is that samples are homogeneous (Grossman and Krueger, 1995), and most studies assume that a sample's economic structure and resource endowments are thus homogeneous. However, this assumption is difficult to satisfy in reality, resulting in the EKC test's "heterogeneity" problem. To overcome this issue, some scholars have conducted EKC tests by grouping samples. For example, Hou et al. (2020) divided forest areas into five major regions based on differences in topography and resource endowments and then analyzed the relationship between forest quality and economic growth in different regions of China based on the EKC framework. However, the basis of this grouping method and the critical value selection is highly subjective. A few studies have used the threshold effect model to automatically identify the endogenous characteristics of data to replace exogenous grouping and divide samples more scientifically (Yu and Zhang, 2016; Hou and Yao, 2019a, 2019b). This method can overcome the impact of the randomness and subjectivity of traditional exogenous grouping on research results.

Overall, limitations remain in the existing research. First, promoting the growth of forested areas has long been the focus of forest policy and research, although quantitative research on the relationship between forest fragmentation and economic growth remains limited, and few if any studies analyze the association at the county level. Second, most quantitative data on forest resources are based on China's National Forest Resources Inventory (NFI) data. NFI data are of great significance for assessing forest resources but are only released every five years. In comparison, satellite remote sensing images can provide more accurate and timely information on forest resources. In addition, ignoring the homogeneity assumption of the EKC may lead to biased empirical results, and traditional subjective exogenous grouping cannot solve this problem. Given the above problems, this study considers the homogeneity assumption of the EKC using a novel grouping approach. Moreover, it empirically analyzes the relationship between forest fragmentation and economic growth in counties with different levels of economic development in the BTH region, thereby enriching and expanding the research on forest fragmentation.

3. Methods

3.1. Forest fragmentation measurement method

Some scholars have measured the degree of forest fragmentation by establishing forest fragmentation models (Li et al., 2010; Li et al., 2011); however, this approach is complicated, and its reliability remains unclear. With the development of research on the landscape structures and functions of forest ecosystems, landscape metrics have been widely used to study forest landscape fragmentation. It has the advantage of considering the ecological significance, correlation between indicators, sensitivity to spatial and temporal differences in landscape patterns, and sensitivity to remote sensing data resolution (Tang et al., 2012; Zhang et al., 2013). Therefore, this study uses a landscape metrics-based method to measure the degree of forest fragmentation.

The landscape metrics-based method uses satellite remote sensing images and GIS analysis technology, which can be used to measure and analyze the degree of forest fragmentation in a specific study area. Satellite remote sensing technology provides information on the spatial distribution of land use and vegetation types. The general steps of the method are as follows. Initially, the satellite remote sensing image is processed to derive the forest distribution image, and then FRAGSTATS software is used to calculate the forest fragmentation index. In this study, land cover categories (forest, grassland, farmland, bare land/building land, and water bodies) were selected as training samples using Landsat satellite remote sensing images and ultrahigh spatial resolution images from Google Earth. The machine learning model classifier by ENVI software was used to train the spectral eigenvalues of different land cover categories on the satellite remote sensing image. Then, all the pixels of the entire image are classified individually to output the classified image. Classification result correction and accuracy analysis were then performed. Finally, FRAGSTATS was used to calculate the forest fragmentation index using the ArcGIS platform. The detailed procedure is as follows.

(1) Land cover category sample selection. There are seven bands of satellite remote sensing images with atmospheric correction: a blue band (450–520 nm (nm)), green band (520–600 nm), red band (620–690 nm), near-infrared band (760–960 nm), mid-infrared band (1550–1750 nm), thermal infrared band (1040–1250 nm), and mid-infrared band (2080–3350 nm). The reflectivity of the different land cover categories in the various wavebands is different. False color synthesis processing was performed to facilitate the identification of different land cover category features. After selecting land-cover samples from Google Earth and importing the parcel range into ENVI, the differences in the characteristics of different land-cover categories can be observed on the image.

(2) Computation classification. Before classification, the separability of the samples was calculated to determine whether they were usable. After testing the sample, it was placed into a classifier. This study adopted a support vector machine algorithm, which can divide the separation plane of different datasets and maximize the distance between the sample points and the separation plane. After solving the separation plane, the pixels of the image were recognized individually, and the classification result was output.

(3) Classification results correction. By comparing the results from different years, it was found that the forest distribution extraction results in specific areas deviated from those of previous years. Compared to Google Earth's images, the forest distribution changed in some areas. However, in other areas, the reflection brightness of the shady slopes was lower than that of the sunny slopes. Land cover with similar reflection brightness on shady slopes is easily incorrectly classified as forested land. To eliminate the errors caused by sample selection, forest land samples were extracted from each period. The forest land training samples were obtained by sampling and then placed into the classifier for secondary classification to obtain revised forest land distribution data. We used a neural network algorithm for this classification that is suitable for the secondary classification of large samples. Crucially, the neural network algorithm can simulate the artificial decision-making process, which is further justified by the classification verification accounting method that this algorithm can better solve the misclassification problem.

(4) Precision analysis. The classified images were compared with actual ground objects. Using the fuzzy matrix method, the overall classification accuracy of each image was >80%, and the kappa coefficient was >0.7. The user accuracy was between 81.83% and 99.92%, indicating that 81.83%–99.92% of the pixels classified as forest land were accurate.

(5) Calculation of forest fragmentation index. Based on the research of Yu et al. (2020), Zhang et al. (2013), and Su et al. (2014), landscape metrics was used as a proxy variable for forest fragmentation to measure the degree of forest fragmentation using FRAGSTATS.

3.2. Model specification

3.2.1. EKC model specification for forest fragmentation

The EKC is a theoretical hypothesis that describes the non-linear relationship between environmental quality and economic growth. Shafik and Bandyopadhyay (1992) argued that the EKC should first be set as a cubic curve. If the cubic curve form was insignificant, the cubic term was removed, and the quadratic curve form was tested. If the quadratic curve form remained insignificant, it fit the linear model. Under this model setting, the EKC is not limited to the "U" or inverted "U" shape but may also be an "N," inverted "N," or other shapes. Through logarithmic processing of each variable to reduce heteroskedasticity, the EKC model of forest fragmentation can be set as follows:

$$LPD_{it} = \beta_0 + \beta_1 lnPGDP_{it} + \beta_2 (lnPGDP_{it})^2 + \beta_3 (lnPGDP_{it})^3 + \delta_i Z_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where PD_{it} is the explained variable, indicating the degree of forest fragmentation, $PGDP_{it}$explains per capita GDP, and Z_{it}shows the vector of the control variables, including the natural logarithm of the population density (lnPOP_{it}), sown area (ln$CROP_{it}$), electricity consumption per capita (ln$ELEC_{it}$), and a dummy variable for implementing the sloping land conversion program ($SLCP_{it}$).β_1,β_2,β_3, and δ_i are the coefficients, and ε_{it} is the error term. For Model (1), the forest fragmentation EKC presents different shapes when $\beta_1\beta_2\beta_3$ take different values, as shown in Table 1.

Many explanatory variables were included in the model; therefore, correlations or multicollinearity among the variables may occur. The Variance Inflation Factor (VIF) method is typically used to detect multicollinearity. In the VIF method, $1/(1 - R_j^2)$ is the VIF of the jth variable and R_j^2 represents the determination coefficient obtained by regressing the jth variable as the dependent variable with the remaining independent variables. The larger the VIF value, the stronger the correlation between this variable and other independent variables (Zhu et al., 2020). It is generally believed that when the VIF value is >5 or 10, the model has a serious multicollinearity problem (Li et al., 2013).

3.2.2. Threshold regression and grouping

Threshold effect refers to a structural change in the direction or quantity of another economic parameter when it reaches a specific critical value. The threshold value is the critical value of economic parameters. The core idea of threshold regression is to determine the critical value that leads to a sudden change in the economic system structure. Structural changes are endogenous within economic systems (Yu and Zhang, 2016). The basic model of Hansen's (1999) panel threshold regression is as follows:

$$y_{it} = \mu_{it} + \beta_1^{'} x_{it} + \varepsilon_{it}, q_{it} \le \gamma; y_{it} = \mu_{it} + \beta_2^{'} x_{it} + \varepsilon_{it}, q_{it} > \gamma \quad (2)$$

where q_{it} is the threshold variable, γ is the threshold value, and the error term ε_{it} is independently and identically distributed. The model can be further simplified as follows:

$$y_{it} = \mu_{it} + \beta_1 x_{it} \times I(q_{it} \le \gamma) + \beta_2 x_{it} \times (q_{it} > \gamma) + \varepsilon_{it} \quad (3)$$

where β_2 represents the coefficients estimated for the threshold variables at different intervals, and $I(\cdot)$ is an indicator function; if the expression in parentheses is true, the value is 1, otherwise, it is 0. After average and individual effect processing, the matrix form of the model becomes: $Y_{it}^* = \beta X_{it}^*(\gamma) + \varepsilon_{it}^*$. At this time, a two-step method can be used for estimation: (1) take the value of γ as a given value, and use Ordinary Least Squares (OLS) for consistent estimation to obtain the estimated coefficients $\widehat{\beta}(\gamma)$ and residual sum of squares of the regression $S_0(\gamma)$; (2) for $\gamma \in \{q_{it} : 1 \le i \le n, 1 \le t \le T\}$, determine the value of γ by identifying the minimum value of $S_0(\gamma)$.

Two tests must be performed after the threshold value is obtained. The first is to test whether the threshold effect is significant. The null hypothesis is $H_0 : \beta_1 = \beta_2$ and the LM statistic is constructed as $F_1 = (S_0 - S_1(\widehat{\gamma}))/\widehat{\sigma}^2$, where S_0 is the residual sum of squares obtained under the null hypothesis. Hansen (1999) suggests a bootstrap method to obtain an asymptotic distribution to construct the *p*-value. The second is to test whether the estimated threshold value equals the true value. The null hypothesis is $H_0 : \gamma = \widehat{\gamma}$ and the likelihood ratio statistic is $LR_1(\gamma) = (S_1 - S_1(\widehat{\gamma}))/\widehat{\sigma}^2$. Hansen (1999) proved that with a significance level α, the confidence interval γ can be solved according to $LR(\gamma) \le c(\alpha) = -2$ ln $[1 - sqrt(1 - \alpha)]$. Hansen (1999) gives critical values of 6.53, 7.35, and 10.59 for the LR statistics of 10%, 5%, and 1%, respectively. The estimation process and hypothesis testing steps of the basic threshold model can be extended to a multiple-threshold case. Based on whether the threshold variable q_{it} exceeds the threshold value, the research samples can be divided into different groups of sample intervals (Yu and Zhang, 2016).

Table 1
EKC shape.

Model	β	EKC features
Linear function	β_1>0 , β_2=β_3=0	Monotonically increasing
	β_1<0 , β_2=β_3=0	Monotonically decreasing
Quadratic function	β_1>0 , β_2<0,β_3=0	Inverted "U"-shaped Curve
	β_1<0 , β_2>0,β_3=0	"U"-shaped Curve
Cubic function	β_1>0 , β_2<0,β_3>0	"N"-shaped Curve
	β_1<0 , β_2>0,β_3<0	Inverted "N"-shaped Curve

3.3. Data source and description of variables

Given our research question and objective, we conducted this study at the county level in the BTH region. This prevents the sample size from being too small for large research objects (e.g., municipal level). Though this affects the robustness of the measurement results, it avoid the difficulty of obtaining forest fragmentation measurement data and socioeconomic data for small research objects (e.g., township level).

The BTH region's forest resources are mainly distributed in the northern and western regions. Due to data availability, five periods of Landsat 5 and Landsat 8 remote sensing images from 2000, 2005, 2010, 2015, and 2018 were selected to measure the degree of forest fragmentation in the 36 sample counties. A spatial resolution of 30 m was selected, and the positions of all pixels precisely matched the ground position (within 10 m). According to the county-level administrative boundaries announced by the state, the number of satellite image pixels within each county can be counted, and the forest coverage of the county in a certain year can be obtained. Thus, satellite remote sensing and socioeconomic data can be matched precisely. The original image data for this study were satellite remote sensing images with cloud occlusion of <5% from the end of June to the end of August each year. During this period, broadleaved and coniferous forests have similar reflectance spectra, thus avoiding the misidentification of broad-leaved forests as other land-use types during spring and winter.

The specification of variables is as follows. Based on Li et al. (2021), the patch density index (PD) is used as a proxy variable for the level of forest fragmentation. The calculation formula is $PD = N/A$, where N is the total number of patches in a certain type of landscape, and A is the total landscape area. A larger PD means greater patches per unit area and greater forest fragmentation. The explanatory variable is GDP per capita ($PGDP_{it}$),adjusted to the constant 2000 price through the GDP deflator. Population density (POP_{it})is used to control the impact of demographic factors on forest fragmentation, grain output per sown area ($CROP_{it}$) measures the level of intensive land use, electricity consumption per capita in rural areas ($ELEC_{it}$)is used to measure the energy transition, and the implementation of the Sloping Land Conversion Progra, ($SLCP_{it}$) is a dummy variable. If a sample county i has implemented the SLCP in year t, the variable will be assigned a value of 1. Otherwise, it will be assigned a value of 0. Socio-economic development data were obtained from the China Rural Statistical Yearbook and the China Statistical Yearbook (Township) of previous years. The summary statistics of the variables are shown in Table 2.

4. Results

4.1. Multicollinearity test

Considering the large number of explanatory variables in this study, simultaneously including them in an econometric model may cause a multicollinearity problem. We used the VIF method to test for multicollinearity. It is generally assumed that VIF values less than the threshold of 10 is acceptable. The multicollinearity test results showed that the maximum VIF value in the explanatory variables was 2.02, and the minimum was 1.17, indicating no serious multicollinearity problems between variables. Thus, regression analysis can be performed.

4.2. Threshold regression results

Based on the panel threshold regression model, this study first tested for the threshold effect on per capita GDP. The threshold values and confidence intervals were calculated to determine whether there is a threshold effect. A consistency test of the threshold value was also conducted to confirm.

Table 3 shows the test results of the threshold effect of GDP per capita in Model (3), in which the F value represents the likelihood ratio test statistic, and the *P* value is the accompanying probability value calculated after 1000 repeated samples. As shown in Table 3, when GDP per capita was used as the threshold variable, the single threshold passed the significance test at the 1% level, whereas the double threshold failed the significance test. Thus, the single-threshold result was confirmed. As Fig. 1 shows, the LR value corresponding to the threshold estimate of per-capita GDP was significantly smaller than the critical value of 7.35, indicating that the threshold estimate was effective.

4.3. Threshold grouping results

Grouping was performed according to the threshold values. The GDP per capita corresponding to the single threshold value was 16,145.55 CNY; therefore, the BTH county samples could be divided into high-income (GDP per capita >16,145.55 CNY) and low-income (GDP per capita ≤16,145.55 CNY) groups. Based on prior research (Yu and Zhang, 2016), the mean value method and the maximum proportion state of the variable method were used to address the "group jumping" problem caused by the period in the panel data and achieve precise grouping. For example, Jingxing County was in the low-income group in 2000 and 2005 but was in the high-income group in 2010, 2015, and 2018. Meanwhile, over 60% of the Jingxing county sample belonged to the high-income group; thus, Jingxing County was classified into the high-income group. Other counties were grouped in a similar manner. Based on this grouping standard, the samples were divided into two groups: 23 sample counties in the low-income group and 13 sample counties in the high-income group.

Table 2
Summary statistics.

Variable	Mean	Std. Dev.	Min	Max
PD	1.69	0.70	0.01	3.04
PGDP	9.37	0.77	7.74	11.16
POP	5.02	0.66	3.66	6.40
CROP	1.53	0.39	0.24	2.11
ELEC	5.61	0.97	3.73	8.19

The values are from already transformed variables.

Table 3
Threshold effect test.

Threshold test	Threshold value	95% confidence interval	F value	P value
Single Threshold	9.6894	[9.6637 , 9.6956]	29.52***	0.0000
Double threshold	9.6894 10.174	[9.6637 , 9.6956] [10.061 , 10.177]	29.52*** 11	0.0000 0.134

The F value and the critical values of 10%, 5%, and 1% in the table are obtained by 1000 repeated samples using "self-sampling"; ***, **, and * represent 1%, 5%, and 10% significance level, respectively.

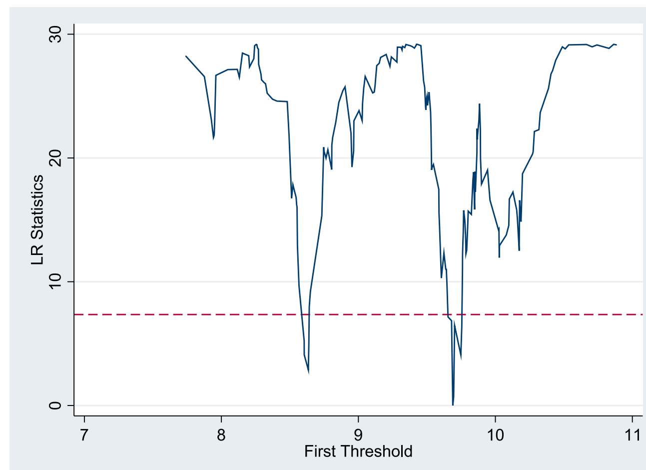

Fig. 1. Threshold value test of GDP per capita.

4.4. Regression results for the EKC hypothesis

Based on Model (1), the forest fragmentation EKC under different economic development levels is discussed considering the threshold effect. A forest fragmentation EKC test was conducted for each group according to the threshold grouping results.

A cubic function was first applied in the panel model regression analysis to test whether the regression coefficients were significant. If the cubic function coefficient was not significant, a quadratic function was applied to test the regression coefficient. If the coefficient of the quadratic function was not significant, a linear regression model was thus applied. Regarding the model's significance and goodness of fit, Table 3 shows that the cubic function regression model is more suitable for the low- and high-income groups.

A Hausman test was conducted to determine whether to use fixed- or random-effects models. Table 4 presents the test and estimation results. The *p*-values of the Hausman test for the two groups were 0.0000 and 0.0695, respectively, indicating the null hypothesis of "applying the random effect model" could be rejected at the 10% significance level. Thus, a fixed-effects model was applied in the regression. The regression results are shown in Columns (5) and (6) of Table 4. Because there are significant differences in the turning point values and coefficient estimations between the different groups, each group's EKC characteristics and forest fragmentation trends are discussed.

(1) Low-income group. This group includes 23 sample counties, and the empirical results show that its forest fragmentation EKC is an inverted "N" shape. For the low-income group, forest fragmentation gradually decreased with economic growth during the early stages of economic development. Forest fragmentation will increase after reaching the first turning point, then decrease after the second turning point. For the 2018 sample values, the minimum GDP per capita was 10,776.5 CNY, crossing the first turning

Table 4
Forest fragmentation EKC test results.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Low-income group	High-income group	Low-income group	High-income group	Low-income group	High-income group
Estimation model	FE	RE	FE	RE	FE	FE
ln*PGDP*	0.229*	0.145	3.099*	0.279	−46.94**	68.60**
	(0.117)	(0.137)	(1.572)	(1.320)	(20.65)	(24.18)
(ln*PGDP*)^2			−0.156*	−0.00659	5.440**	−7.014**
			(0.0841)	(0.0684)	(2.348)	(2.513)
(ln*PGDP*)^3					−0.208**	0.238**
					(0.0885)	(0.0867)
Control variables	Control	Control	Control	Control	Control	Control
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Hausman test	27.42	8.08	31.88	9.75	33.6	13.11
	[0.0001]	[0.2321]	[0.0000]	[0.2034]	[0.0000]	[0.0695]
Observations	115	65	115	65	115	65
R-squared	0.562	0.7513	0.570	0.7522	0.579	0.784
EKC curve	–	–	–	–	Inverted "N"	"N"
Turning point					2529.44	9632.67
Turning point					14,766.93	35,388.55

Robust standard errors are in parentheses and the corresponding p-values are in square brackets.

point, and indicating that all sample counties in this group crossed the first turning point. The highest GDP per capita in the sample counties was 25,875.2 CNY, crossing the second turning point. More specifically, the GDP per capita of 15 sample counties in 2018 crossed the second turning point, indicating that forest fragmentation will decrease with economic development in these sample counties. The GDP per capita of the remaining eight sample counties does not cross, but is close to the second turning point (as shown in Table 5). Using the trend extrapolation method, the economic growth forecast of the eight sample counties indicate that it will take up to five years to cross the second turning point. For the eight sample counties, forest fragmentation will increase with economic growth in the short term and decrease after crossing the second turning point.

(2) High-income group. This group includes 13 sample counties, and the empirical results show that its forest fragmentation EKC is an "N" shape. For the high-income group, forest fragmentation increases with economic growth during the early stages. Forest fragmentation decreased after crossing the first turning point and then begins to increase as GDP per capita crosses the second turning point. From the 2018 sample values, the minimum GDP per capita of the sample counties was 17,239.4 CNY, crossing the first turning point, and indicating that all sample counties in this group crossed the first turning point. The highest GDP per capita in the sample counties in 2018 was 64,659.5 CNY, crossing the second turning point. Meanwhile, 10 sample counties lie between the two turning points, and the forest fragmentation of the 10 sample counties decreases with economic growth. The GDP per capita of the other three counties crossed the second turning point, indicating that forest fragmentation will increase with economic growth.

(3) Based on the average annual growth rate of GDP per capita from 2000 to 2018, we predicted the time required for the sample counties to cross the second turning point using the trend extrapolation method. Thus, future forest fragmentation trends in different sample counties could be analyzed. The predicted results are shown in Table 5. For the sample counties in the low-income group that did not cross the second turning point, the GDP per capita was relatively close to the turning point. For these sample counties to cross the second turning point could take up to five years, and forest fragmentation will decrease with economic growth after crossing the turning point. Counties in the high-income group that did not cross the second turning point were divided into two categories. The first category of seven sample counties, whose GDP per capita is close to the turning point, should cross the second turning point in the next four years and thus experience an increase in forest fragmentation with economic growth. The second category of three sample counties, whose GDP per capita is far from the second turning point, should cross the second turning point in at least 10 years. In the short term, forest fragmentation decreases with economic growth in these sample counties.

Table 5
Prediction of sample counties to cross the second turning point.

Shape	ID	Time required to cross the second turning point	GDP per capita when crossing the second turning point	current stage
Inverted "N"	19	1 year	14,950.61	rise
Inverted "N"	20	4 years	15,732.68	rise
Inverted "N"	21	1 year	15,094.32	rise
Inverted "N"	22	2 years	15,408.56	rise
Inverted "N"	23	5 years	15,031.06	rise
Inverted "N"	28	4 years	15,172.20	rise
Inverted "N"	29	4 years	15,440.65	rise
Inverted "N"	34	2 years	15,850.38	rise
"N"	6	1 year	36,315.10	fall
"N"	7	11 years	37,386.50	fall
"N"	8	10 years	35,599.96	fall
"N"	9	3 years	37,424.54	fall
"N"	12	1 year	38,210.81	fall
"N"	15	2 years	35,556.12	fall
"N"	17	13 years	36,892.01	fall
"N"	18	2 years	38,362.55	fall
"N"	32	4 years	37,771.30	fall
"N"	39	2 years	36,391.56	fall

4.5. Robustness test

A robustness test was conducted by replacing the forest fragmentation index. We replaced the explanatory variable of PD with the Landscape Shape Index (LSI) (Zhang et al., 2013; Su et al., 2014), which is also widely used to measure the degree of forest fragmentation. If the coefficients and significance are consistent with the model results in the previous section, the model estimation results are robust and reliable.

LSI is a landscape pattern index that describes the complexity of a landscape shape by calculating the degree of deviation between the patch shape and a square of equal area. The larger the LSI value, the more irregular the patch shape in the landscape and the higher the degree of forest fragmentation.

The test was conducted from two perspectives. The first replaces the explained variables without changing the grouping, and the second changes the grouping based on the endogeneity of the threshold effect. The robustness test for replacing the explained variables with the LSI is shown in Table 6.

4.5.1. Original grouping test

From the regression results, when the forest fragmentation index is changed without changing the grouping, the EKC relationship between forest fragmentation and economic growth and the significance of the variables are consistent with the benchmark results, indicating that the benchmark estimation results were robust.

4.5.2. New grouping test

As the proxy variable of the explained variable was replaced, the samples were regrouped using threshold regression to comply with the internal grouping characteristics of the threshold effect. As shown in Table 7, when the LSI is used as the explained variable, only one threshold value exists. Fig. 2 shows that the threshold values passed the consistency test. The GDP per capita corresponding to a single threshold value was 17,770.59 CNY, and the sample counties were regrouped according to the grouping method described in Section 4.3. Under the new grouping, the low-income group contains 26 sample counties and the high-income group 10 sample counties.

Table 8 shows the regression results of the robustness test. After changing the proxy variables of forest fragmentation and regrouping, the EKC relationship between forest fragmentation and economic development and the significance level of each variable remain consistent with the benchmark results above, indicating that the estimation results in this study are robust.

5. Discussion

Heterogeneity exists in the relationship between forest fragmentation and GDP per capita. The test results of the forest fragmentation EKC of counties in the BTH region were significantly different between this study and other empirical studies without grouping. For example, in a study without grouping the forest fragmentation EKC of counties in the BTH region showed an inverted "U" shape based on GDP per capita (Li et al., 2021). In this study, when the threshold regression model was used to group the samples according to economic development level, the EKC of the low- and high-income groups showed inverted "N" and "N" shapes, respectively. The EKC test assumes sample homogeneity; however, there is heterogeneity in the BTH region's sample economies with different development levels. If the sample is regressed without considering sample heterogeneity, it is difficult to identify the trend. Hence, when examining the nonlinear relationship between forest fragmentation and economic growth, it is necessary to consider different regions' economic development level to provide a more accurate explanation.

For low-income sample counties with an inverted "N" shape, forest fragmentation decreases, increases after the first turning point, and decreases after the second turning point with an increase in GDP per capita. In the initial stages of economic growth, the energy transition triggered by economic development greatly reduces deforestation (Bhattarai and Hammig, 2001), playing a positive role in curbing forest fragmentation. During this stage, forest fragmentation decreases with an increase in GDP per capita. As the economy continues to develop, the intensity of forest resource utilization increases (Shen et al., 2013), and higher consumption levels put more pressure on forest resources (Kaika and Zervas, 2013; Wang and Huang, 2015). At this stage, forest fragmentation increases with economic growth. With further economic development, forest governance and citizen environmental protection awareness improves, helping reduce forest fragmentation (Li et al.,

Table 6
Robustness test (1).

Variables	(1) Low-income group	(2) High-income group
ln*PGDP*	−46.85*	30.96**
	(25.60)	(13.98)
$(\ln PGDP)^2$	5.299*	−3.226**
	(2.899)	(1.464)
$(\ln PGDP)^3$	−0.198*	0.111**
	(0.109)	(0.0507)
Control variables	Control	Control
Time fixed effects	Yes	Yes
County fixed effects	Yes	Yes
Observations	115	65
R-squared	0.391	0.770
EKC curve	Inverted "N"	"N"

Table 7
Threshold effect test (2).

Threshold test	Threshold value	95% confidence interval	F value	P value
Single Threshold	9.7853	[9.8458 , 9.8801]	11.04*	0.094
Double threshold	9.8545	[9.8458 , 9.8801]	11.04	0.112
	9.8844	[9.8737 , 9.8905]	14.45**	0.036

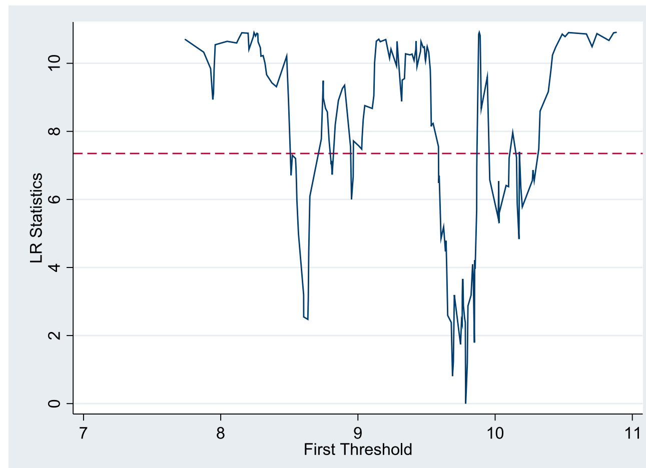

Fig. 2. Threshold value test of GDP per capita (2).

Table 8
Robustness test (2).

Variables	(1) Low-income group	(1) High-income group
ln*PGDP*	−44.77**	43.89**
	(20.89)	(14.85)
$(\ln PGDP)^2$	5.060**	−4.567**
	(2.348)	(1.548)
$(\ln PGDP)^3$	−0.189**	0.157**
	(0.0877)	(0.0534)
Control variables	Control	Control
Time fixed effects	Yes	Yes
County fixed effects	Yes	Yes
Observations	130	50
R-squared	0.434	0.744
EKC curve	Inverted "N"	"N"

2016). According to the sample counties' turning point trend in the empirical results, all sample counties in the low-income group have exceeded or will shortly exceed the second turning point. That is, the degree of forest fragmentation has or will decrease with economic growth.

The findings in this subgroup are similar to those of most existing studies in developing countries, supporting the view that forest quality will eventually improve as long as the economy continues to grow (Ahmed et al., 2015; Ajanaku and Collins, 2021; Zhu et al., 2022). This indicates that low-income counties should focus on the relationship between economic development and forest ecology. The economic development of the Tianjin and Hebei provinces has long relied on secondary industries. Under certain conditions, alternative measures can be taken to further improve forest ecology. First, the impact of a tertiary industry on sustainable land use is believed to be more positive (Barbier, 1997). Therefore, the industry structure could be further optimized to meet the requirements of the BTH coordinated development strategy. Second, it is worth noting that although economic growth is necessary to overcome pollution or ecological deterioration, it is never a sufficient condition (Kaika and Zervas, 2013), nor is it the sole solution (Caravaggio, 2022). Therefore, local governments should encourage forest resource management activities (Basu, 2011).

In the high-income group, the EKC between forest fragmentation and GDP per capita is "N" shaped. The empirical results are consistent with those of the low-income group. The curve was divided into three stages according to the two turning points. The first two stages of the "N"-shaped curve in the high-income group, namely the inverted "U"-shaped stage, corresponds to the inverted "U" shape in the low-income group's last two stages. However, based on the regression results of the high-income group, more attention should be paid to the adverse effects of economic growth on forest fragmentation in the case of high-income levels and rapid economic growth. According to the turning point trend in the sample counties, most of the sample counties in the high-income group have not exceeded the second turning point and are in the inverted "U"-shaped stage. This finding is similar to that of Hou and Yao (2019a, 2019b), which suggest that forest resources and economic growth show an inverted "N" shape.

The results of this study show that most of the sample counties in the BTH region have a coordinated and harmonious economic growth and forest resources development in recent years. However, it is still necessary to strengthen forest management in areas with rapid economic development, especially forest ecological protection in the high-income sample counties that have crossed or are about to cross the second turning point. According to our empirical results, the seven sample counties in the high-income group whose GDP per capita is close to the turning point should cross the second turning point in the next four years. This does not necessarily imply that forest fragmentation will increase in these counties. Measures, such as optimizing the industrial structure, increasing forestry investment, and introducing private capital, can be taken to avoid forest fragmentation in these counties after reaching the second turning point (Hou and Yao, 2019a, 2019b). Maintaining coordinated development between economic growth and forest ecology largely depends on such innovative policies and market measures (Xie, 2017).

Our results call attention to the view that economic development is insufficient for achieving better environmental conditions or inhibiting ecological degradation (Arrow et al., 1996). Therefore, more effort is required to prevent forest fragmentation. Although the present study did not encompass the role of policy interventions, such as forest protection, due to a lack of data, the relevant literature shows that the government plays a key role in the reversal of deforestation (Rudel and Schneider, 2010). Culas (2007) notes that increasing deforestation control by improving governance quality and implementing environmental policies is more persuasive than limiting economic development. Moreover, forests can be protected and regenerated through the participation of forest-dependent people in forest management (Khare et al., 2000; Ballabh et al., 2002). Therefore, forest fragmentation can be reduced by improving citizen awareness of forest protection and by adhering to the concept of green and sustainable development.

Moreover, as Xu et al. (2020) argues, it is dangerous to ignore the existence of an N-type relationship when studying the nonlinear relationship between environmental deterioration and per-capita income. We believe the same is true when investigating the forest fragmentation EKC hypothesis. It is necessary to discuss groups according to different economic development levels, address the heterogeneity problem, and reduce the vulnerability of EKC analysis.

These research findings have important policy implications for future studies. First, the EKC hypothesis was once again proven to exist in the forest fragmentation of sample counties with different income levels in the BTH region. Second, the EKC of forest fragmentation in the sample counties in the BTH region was heterogeneous. Therefore, policymakers should consider the development of counties with different income levels and formulate and implement effective economic development and forest protection policies. This is especially true for high-income counties, which are about to exceed the second turning point to reduce forest fragmentation and improve forest quality.

This study has some limitations. First, although the representativeness of the samples is considered in this study, it should be emphasized that, subject to the complexity of remote sensing image acquisition and image processing, our data only covers 36 sample counties from 2000 to 2018. Second, limited by the availability of statistical data, this study omitted political and institutional variables. Third, the proxy variable for forest fragmentation chosen in this study may not have fully characterized the complex process of forest fragmentation. Therefore, we are cautious about our conclusions. In the future, analysts should seek more comprehensive data, explore more scientific and effective forest fragmentation indices, and cover more space and time to obtain more robust and reliable empirical conclusions.

6. Conclusions

Due to economic development differences among sample counties, the EKC hypothesis on forest fragmentation may suffer from a "heterogeneity problem." Thisproblem directly affects the accuracy of the EKC test results in the BTH region and may even lead to unreliable conclusions and inappropriate policy recommendations. Based on the EKC analysis framework, this study uses the threshold regression method to conduct a grouping study of 36 sample counties in the BTH region from 2000 to 2018, effectively solving the heterogeneity problem in the EKC hypothesis of forest fragmentation. The main conclusions of this study are as follows.

(1) The EKC relationship between forest fragmentation and GDP per capita varies among sample counties with different economic development levels in the BTH region.
(2) In the low-income sample counties, the forest fragmentation EKC is an inverted "N" shape. Most counties in the low-income group have crossed the second turning point and are currently at a stage where forest fragmentation decreases with economic growth. For those yet to cross the second turning point, their GDP per capita is very close to the second turning point, which takes at most five years to cross.
(3) In the high-income sample counties, the forest fragmentation EKC is "N"-shaped. Most sample counties in the high-income group have not yet crossed the second turning point and are currently at a stage where forest fragmentation decreases with economic growth. Those yet to cross the second turning point were divided into two categories: one containing three sample counties whose GDP per capita is far from the turning point, and it takes at least 10 years to cross it; and the other includes seven sample counties whose GDP per capita is close to the turning point, taking at most four years to cross the second turning point.

The findings of this study have important policy implications. First, although the impact of GDP per capita on forest fragmentation varies at different economic development levels, most sample counties in the BTH region are in a stage of coordinated development between economic growth and forest resources. Thus, regional policy should adhere to green and sustainable development principles to improve its forest ecology. Second, more attention must be paid to promoting green development in some high-income counties, and the government must implement targeted policies in counties with different characteristics. Finally, it is necessary to improve citizen environmental awareness. With economic development, citizen awareness of forest ecological protection and their demands for a better ecological environment are important forces in reducing forest fragmentation. It is necessary to stimulate and improve citizen awareness of environmental protection through education and publicity, thus contributing to forest ecological protection and development.

CRediT authorship contribution statement

Dandan Deng: Methodology, Writing – original draft. **Jiayun Dong:** Writing – review & editing. **Yiwen Zhang:** Supervision, Writing – review & editing. **Wenyuan Liang:** Writing – review & editing. **Kun Liu:** Supervision, Writing – review & editing. **Lingchao Li:** Conceptualization, Investigation, Supervision, Funding acquisition.

Declaration of Competing Interest

No conflict of interest exits in the submission of this manuscript, and the manuscript is approved by all authors for publication. I would like to declare on behalf of my co-authors that the work described is original research that has not been published previously, and not under consideration for publication elsewhere.

Data availability

The authors do not have permission to share data.

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