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Forest Fragmentation and Driving Forces in Yingkou, Northeastern China

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Abstract: Forest fragmentation, the process of changing original large and intact forest patches into smaller and isolated areas, significantly influences the balance of surface physical environment, biodiversity, and species richness. Sufficient knowledge of forest fragmentation is necessary to maintain ecological balance and promote sustainable resource utilization. This study combines remote sensing, geographical information systems, and landscape metrics to assess forest fragmentation at landscape and pixel levels during different time periods (2000–2005, 2005–2010, and 2010–2015) in the Yingkou region. Spatial statistical analysis is also used to analyze the relationship between forest landscape fragmentation and its determinants (e.g., natural factors, socioeconomic factors, and proximity factors). Results show that forest patches became smaller, subdivided, and isolated during 2010–2015 at the total landscape level. Local changes occurred in the southwest of the study region or around the development area. Our data also indicate that shrinkage and subdivision were the main forest fragmentation processes during three times, and attrition became the main forest fragmentation process from 2010 to 2015. These changes were significantly influenced by natural factors (e.g., elevation and slope), proximity factors (e.g., distance to city and distance to province roads), and socioeconomic factors (e.g., gross domestic product). Results presented in this study provide valuable insights into the pattern and processes of forest fragmentation and present direct implications for the protection and reasonable utilization of forest resources.

Keywords: land-use change; forest fragmentation; driving forces; forest protection

1. Introduction

As one of the most significant natural resources, global forests cover approximately 40 million km^2 [1]. Forests have attracted attention from numerous studies because of the various basic needs they serve [2], such as providing raw materials for economic activity [3], regulating surface temperature and precipitation, fixing carbon, and serving as a valuable habitat for wildlife [4]. As humans increasingly consume forest resources and expand agricultural areas, forests become vulnerable to area loss and fragmentation [2]. For example, the total global forested area decreased by 3.1% from 1990 to 2015, with a net loss of 70,000 km^2 per year in tropical countries from 2000 to 2010 [1]. Loss of forests contributes to environmental degradation, reduces biodiversity [4,5], and consequently exerts a significant impact on the environmental protection and socioeconomic development [2]. To reverse this situation, the Sustainable Development Goals were widely considered at the United Nations Summit on Sustainable

Development in 2015 [1]. China, as a developing country, has a large population and limited resources. Forest resource is a main type of land use in China that can provide economic (e.g., wood production) and ecological values (e.g., ecosystem services) [4]. Understanding land-use change at various scales [6], especially the fragmentation of forest landscape, is important to promote sustainable land management and maintain ecosystem resilience.

Forest fragmentation is the process by which large and intact forests transform into smaller, isolated, and divisional forest patches [5,7]. Forest fragmentation is a major concern to the international community, mainly because forest fragmentation impacts the energy balance of surfaces or the physical environment and biogeographic changes [8], alters the forest ecosystem function and condition [3], and affects important environmental processes [9], such as global biodiversity, extinction rates, species richness, and other ecosystem characteristics [10–12]. The study of habitat fragmentation provides a significant bridge between landscape ecology and landscape planning [13]. Several researchers introduced numerous metrics, such as area-weighted mean patch area, area-weighted shape index, Euclidean nearest neighbor distance, landscape division, splitting index, and effective mesh size, to measure forest fragmentation at the landscape level [14–17]. These metrics reflect the area, shape, subdivision, and isolation of the landscape and are strongly related to landscape fragmentation [14]. Several studies also assessed landscape fragmentation through neighborhood rules based on the model or modified models of Forman (1995) at pixel level [18–20], as well as through metrics based on the model of Riitters et al. (2000) with window sizes [9,21,22]. However, the application of simple landscape metrics to forest fragmentation phases is limited [15], and the studies at landscape level cannot reflect the detailed degree of landscape fragmentation. In this regard, a comprehensive method should be provided to effectively determine forest fragmentation, including the effective metrics at landscape level and the reasonable rules for data at pixel level.

Forest fragmentation is influenced by intensive human activities and natural disturbances [23], human activities may have a greater effect on forest fragmentation than natural disturbances with land use for different purposes [4,9]. In a forest ecosystem, socioeconomic drivers, such as population growth, economic growth, and land-use management, are significant drivers of forest fragmentation [14,23,24]. Expansion of human settlement areas [15], transport infrastructure [25–28], and change in water surface area [4,29] also influence forest loss or fragmentation. Therefore, the relationship between forest fragmentation, natural resources, and socioeconomic development of a region should be considered in landscape planning and land use management.

The forests of China are at risk of continued degradation and fragmentation [9]. In the past century, three periods of deforestation were recorded from 1986 to 1998 [30]. Although China implemented the Natural Forest Protection Program [30], two Classification-based Forest Management in 1998 [30], and Sloping Land Conversion Program or Grain for Green in 1999 [31] to protect forest resources, the loss of forests did not slow down. Thus, new guidelines are urgently needed to help land-use managers understand the dynamic changes in pattern and processes of forests. Recently, numerous studies in China focused on the pattern and processes of forest fragmentation [14,20,24]. The processes of landscape fragmentation were identified through a fragmentation algorithm with metrics by Jiang et al. (2014) and neighborhood analysis by Li et al. (2015). Liu et al. (2016) selected five metrics to characterize the processes of forest loss and fragmentation. Such studies improved our understanding of forest fragmentation at different levels. Numerous studies assessed the drivers of change in landscape pattern; however, few studies quantified the influential drivers of forest fragmentation [23] and considered the spatial autocorrelation and effect of landscape fragmentation. The socioeconomic drivers of forest fragmentation with statistical data were also considered with minimal regard for the spatial effect of these factors. To date, no comprehensive studies have systematically assessed forest landscape fragmentation and its associated determinants at different scales.

This study adopted remote sensing (RS), geographic information system (GIS), landscape metrics, and spatial statistical analysis to assess the forest fragmentation processes and its driving forces in Yingkou region, northeastern China. Specifically, this study aimed to: (1) accurately characterize the processes of forest landscape fragmentation at pixel level and pattern at landscape level in different time periods; (2) identify the spatial driving factors of forest fragmentation pattern at different scales; and (3) provide several suggestions for land use planning and policies for forest resources management.

2. Materials and Methods

2.1. Study Area

Yingkou region is located in the northwestern part of the Liaodong Peninsula, China. The region covers 5279 km^2, extending from 39°55′ N to 40°56′ N and from 121°56′ E to 123°02′ E (Figure 1). Mountainous areas account for approximately 50% of Yingkou. The topographical distribution is shown in a digital elevation model (30 m; Figure 1), which was provided by the Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Sciences [32]. The region is mostly characterized by a temperate continental monsoon climate, with an average annual temperature ranging from 8.8 °C to 9.3 °C. The mean annual rainfall is approximately 876–1029 mm. Benefiting from these topographic and climatic features, forests present the dominant land cover type in Yingkou region. From 2000 to 2015, the forest area in the region decreased from 46.45% to 45.15% (Table 1).

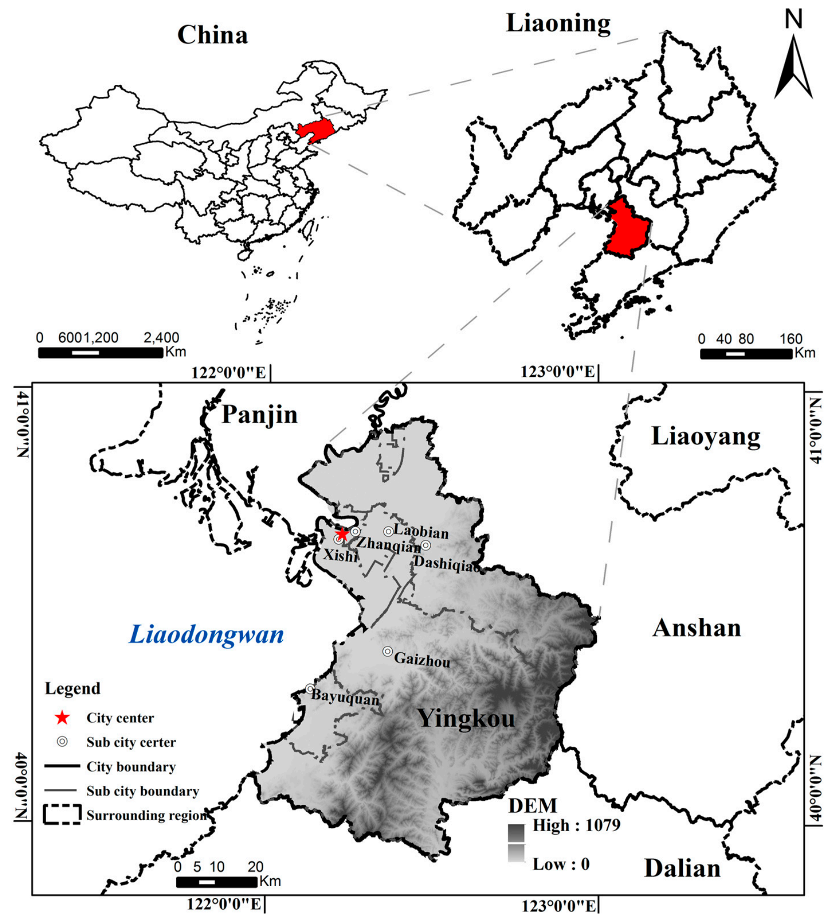

Figure 1. The location and a digital elevation model of the study area.

2.2. Data Processing

Four series of imagery (2000, 2005, 2010 and 2015), including Landsat 5 (resolution: 30 m × 30 m) and Google Earth were used to extract land cover information. Landsat Thematic Mapper images were collected for the years 2000, 2005, and 2010, and Google Earth maps were collected for the years 2000, 2005, 2010, and 2015. First, atmospheric and topographic corrections were conducted in ENVI5.1 software, and the root mean square error was limited to within 0.5 pixels. Data from 2010 were first interpreted, and the land cover maps for the other years were updated based on these data. The eCognition object-oriented classification and the decision tree were used to make the initial classification [33], including cropland, forest, urban, water and other land. In this classification, other land comprised grassland, bare land, and so on. A visual interpretation method with Google Earth and land use maps in 2012 and 2014 were then employed to modify the classifications. Approximately 1200 samples from ground survey data and stratified random sampling were selected during a field survey in 2009 to assess the accuracy of the classification. The overall accuracies were approximately 90%, and the Kappa coefficient was 0.8. The accuracies of all four forest landscape maps were also approximately 90%. The amount and distribution of land cover in four years are shown in Table 1 and Figure 2.

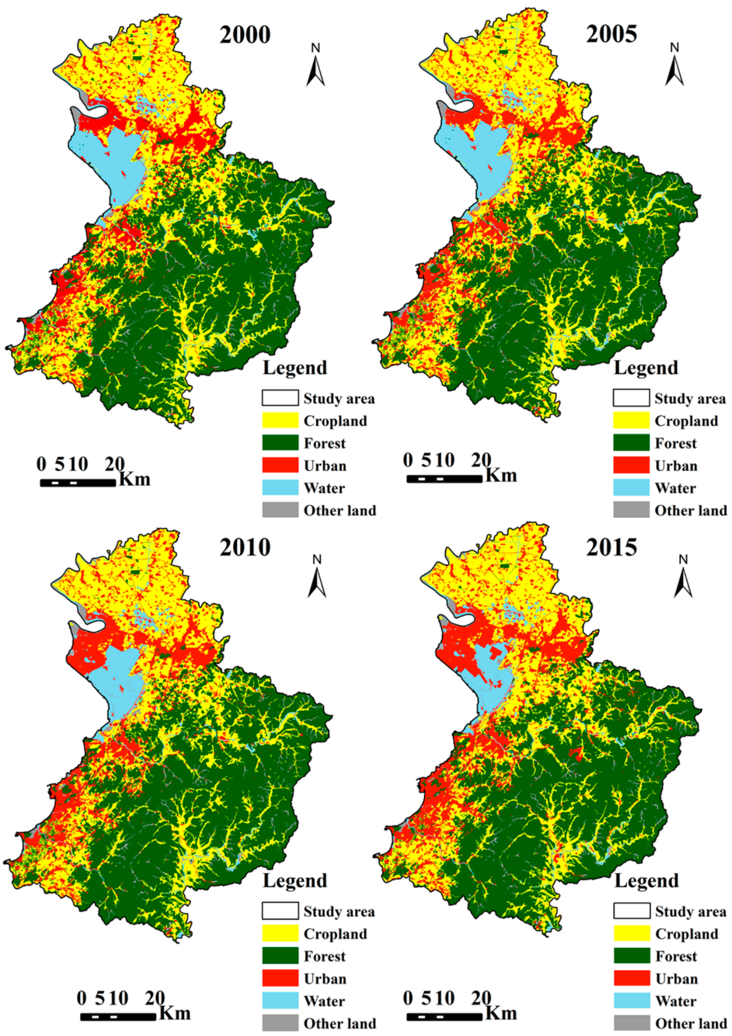

Figure 2. Distributions of landscape cover types of Yingkou, China in 2000, 2005, 2010 and 2015.

Table 1. Land area between 2000 and 2015.

	2000		2005		2010		2015	
	Area (km^2)	Proportion (%)	Area (km^2)	Proportion (%)	Area (km^2)	Proportion (%)	Area (km^2)	Proportion (%)
Forest	1716.78	32.54	1680.50	31.86	1649.79	31.27	1643.44	31.15
Cropland	2450.11	46.45	2439.69	46.25	2436.86	46.20	2381.98	45.15
Urban	656.49	12.45	699.51	13.26	792.46	15.02	900.94	17.08
Water	359.13	6.81	363.35	6.89	299.33	5.67	262.12	4.97
Other land	92.62	1.76	92.08	1.75	96.69	1.83	86.65	1.64
Total	5275.13	100.00	5275.13	100.00	5275.13	100.00	5275.13	100.00

Roads (highways, national ways, province ways, and county ways) and rivers were obtained from the historical traffic maps of Liaoning. Maps of Google Earth in 2000, 2005 and 2010 were used to modify the road and river datasets via the visual interpretation method (Figure 3).

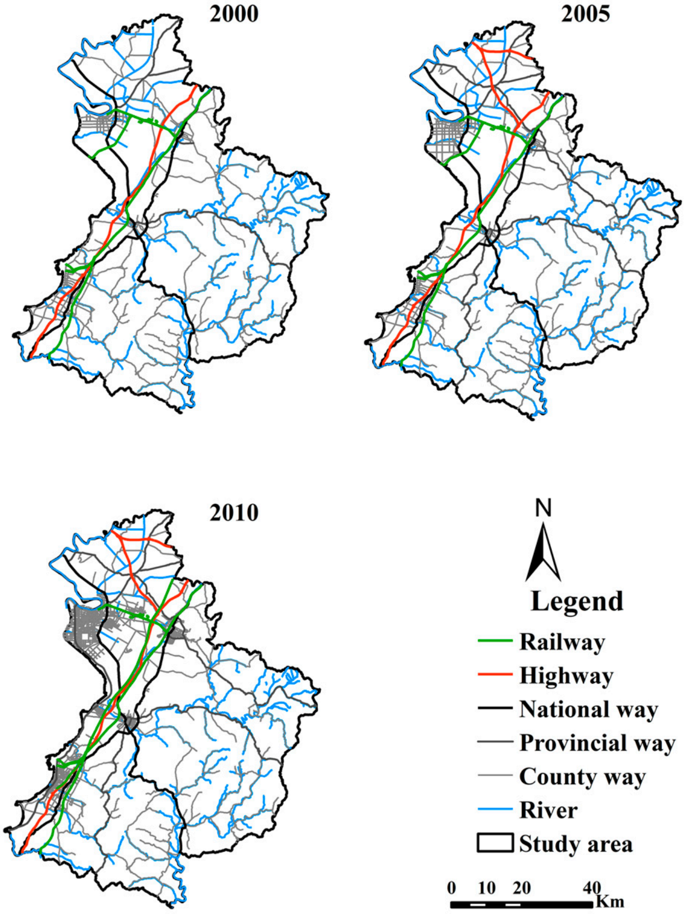

Figure 3. Distributions of roads and rivers of Yingkou region, China in 2000, 2005 and 2010.

The dataset of the social and economic database (Figure 4), contained population and gross domestic product (GDP) data at 1 km × 1 km scale, was provided by Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences [34].

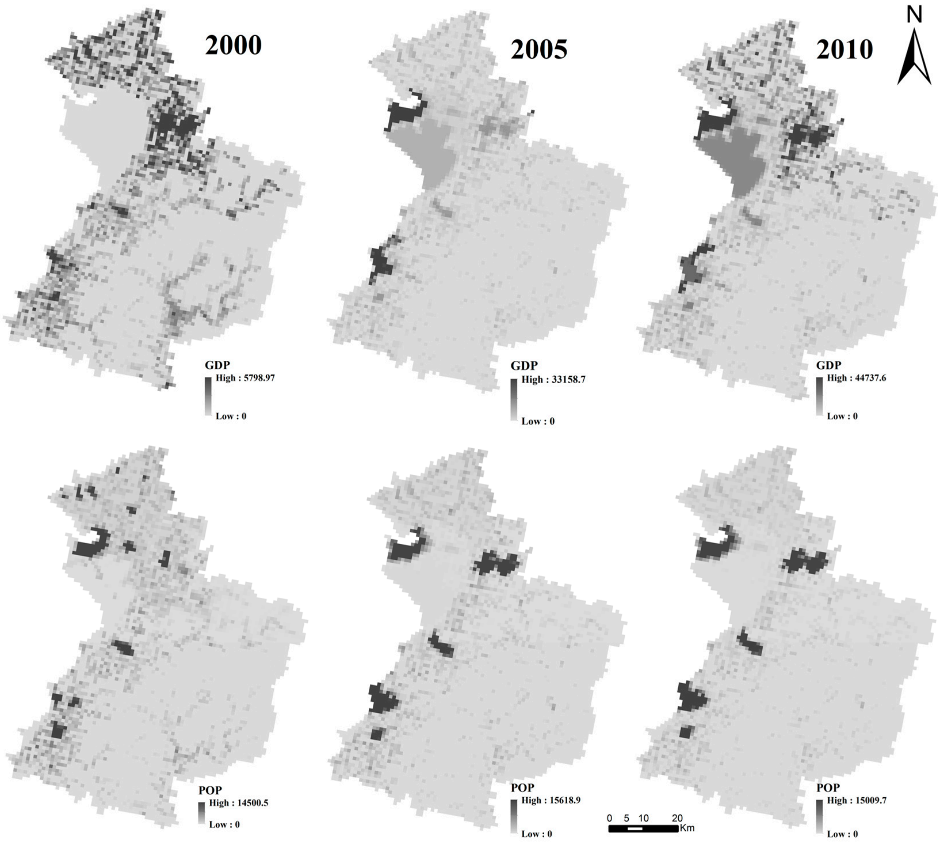

Figure 4. Distributions of population (POP) and gross domestic product (GDP) of Yingkou region, China in 2000, 2005 and 2010.

2.3. Forest Fragmentation Pattern at Landscape Level

In this study, the forest fragmentation pattern at landscape level was described using the following six metrics documented in the related studies of Jaeger (2000) and Liu et al. (2016): (1) area-weighted mean patch area (AREA_AM); (2) area-weighted shape index (SHAPE_AM); (3) mean Euclidean nearest neighbor index (ENN_MN); (4) landscape division index (DIVISION); (5) effective mesh size (MESH); and (6) splitting index (SPLIT). These six metrics reflect the patch size, shape, isolation, and subdivision, which are closely related to landscape fragmentation. When AREA_AM, SHAPE_AM, and MESH decrease, and ENN_MN, DIVISION, and SPLIT increase, the forest becomes smaller, regular, subdivided and isolated. These metrics were calculated at different scales such as sampling blocks of 2 km $\times$ 2 km and 10 km $\times$ 10 km, and the complete study area. Each of these metrics was calculated using Fragstats 4.2.

2.4. Forest Fragmentation Processes at Pixel Level

This study assessed the processes of landscape fragmentation at pixel level from Forman (1995) and the model of Li and Yang (2015). Forest patches converted from urban land, cropland, water or other land were regarded as forests in the measurement procedure. The spatial processes of landscape fragmentation, including perforation, subdivision, shrinkage, and attrition, were identified using a modified version of the model by Li and Yang (2015). Perforation is visible in the original forest patches, while shrinkage and subdivision always occur in the middle phases of landscape change [18]. Attrition occurs in the isolated forest patches. This method detects the spatial relationship between the lost and remaining areas of forest, to identify the different spatial processes of forest fragmentation, which have different impacts on the ecosystem [20]: for example, perforation and subdivision may result in a decrease in average size and an increase in total boundary length. Shrinkage and attrition may result in a decrease in total boundary length; however, attrition also causes a decrease in patch number [18].

2.5. Driving Factors of Forest Fragmentation

Natural factors, socioeconomic factors, and land use policies are generally the determinants of forest fragmentation [4,23]. Natural factors, such as climate, hydrology, and topographic condition, are the primary variables that impact ecological processes [7,22]. The topographic condition may significantly affect the forest fragmentation of a region; therefore, two topographic factors (elevation and slope) were selected for consideration. The driving forces of socioeconomic factors, such as demographic conditions and economic development [14,22–24], are important macro-factors that influence landscape fragmentation, hence, two socioeconomic factors (population and gross domestic product) were selected for consideration. In addition, road [25,26], river [4], urban expansion [15], and other human activities are major forces of landscape fragmentation; therefore, the following eight proximity factors were selected to reflect the spatial relationship between the responsible determinants and forest fragmentation: distance to city center, distance to towns, distance to railways, distance to highways, distance to national ways, distance to provincial ways, distance to county ways, and distance to rivers.

For the topographic factors, the average values of the slope and elevation of the assessed unit were calculated using a digital elevation model (Figure 1). All proximity factors were calculated based on the Euclidean distance tool in ArcGIS. Population and gross domestic product data were resampled from the dataset of the social and economic database (Figure 4).

The analysis of spatial data is a step before suggesting dynamic factors to explain the spatial pattern and before estimating more complicated regression models [35]. Spatial autocorrelation is one of the primary problems in spatial data analysis [36]. The degree of spatial autocorrelation can be measured by Moran's I. A positive Moran's I value (value more than 0) indicates a general pattern of clustering in a space of similar values [35]. In the current study, the global Moran's I was used to measure the degree of spatial autocorrelation of forest fragmentation at landscape level.

Spatial regression models were used to reflect the relationship between landscape changes and their determining factors [37], especially spatial error model and spatial lag model. These two models can identify the spatial factors of landscape change, because they consider spatial dependence and effect. Spatial error model incorporates spatial error dependency, whereas spatial lag model considers spatial lag dependency [37]. Therefore, spatial error model and spatial lag model were used in this study. Spatial error model argues that the dependent variable depends on a set of local indicators and that the error terms are spatially auto-correlated [38]. The model can be expressed as follows [35]:

$$\begin{gathered} \varepsilon = \lambda W \varepsilon + u \\ y = X\beta + \varepsilon \end{gathered}$$

where ε is a vector of spatially auto-correlated error terms, λ is the spatial autocorrelation coefficient, W is a spatial weight matrix that describes the spatial arrangement of all the spatial units, u is a vector of independently and identically distributed error terms, y is a vector of observations on the dependent variable (the landscape pattern of forest), X is a row vector of spatial characteristics, and β is a matching vector of fixed parameters.

Spatial lag model considers that the event rate in the focal region is jointly determined with that of neighboring regions. The equation can be expressed as follows [35]:

$$y = \rho W y + X\beta + \varepsilon$$

where ρ is the spatial autoregressive, and Wy is a spatially lagged dependent variable for weights matrix W.

One of the proper measures of fit of the spatial model is Akaike Info Criterion (AIC), where the lower the value of AIC, the better the fit of the model [35]. Therefore, AIC was used to compare the performance of the two models.

Natural factors, proximity factors, and socioeconomic factors are independent variables, whereas landscape metrics are dependent variables. Each variable was first standardized and normalized via a z-score standardization method. Independent variables were tested by variance inflation factors to avoid multicollinearity and variable redundancy. The global autocorrelation analysis and all regression models were performed on GeoDa1.6.7 software.

3. Results

3.1. Forest Change

The substantial changes in forest landscape during 2000–2015 were calculated through the overlay analysis of four land use maps by ArcGIS and are illustrated in Table 2. During these periods, forests exhibited sharp loss and few gains, especially during 2010–2015. However, the gross changes of forests increased annually.

Table 2. Forest change between 2000 and 2015.

	Increased Amount (km^2)	Increased Rate (%)	Decreased Amount (km^2)	Decreased Rate (%)	Gross Change Rate (%)
2000–2005	2.35	0.02	12.77	0.10	0.12
2005–2010	6.92	0.06	9.75	0.08	0.14
2010–2015	9.41	0.08	64.29	0.53	0.61

3.2. Forest Fragmentation Pattern at Landscape Level

At the total forest landscape level (Figure 5), area-weighted mean patch area, area-weighted shape index, and effective mesh size decreased from 2000 to 2005, increased from 2005 to 2010, and decreased from 2010 to 2015; the change trends of mean Euclidean nearest neighbor index, landscape division index, and splitting index were the opposite. These results showed that the forest landscape was more subdivided, isolated, and regular in the period of 2010–2015. Upon comparing all the selected metrics at different scales and times (Appendix A), the value changes were all concentrated in the southwest of the study region or around the development area. These data indicated that the western area experienced a significant amount of landscape change and forest fragmentation.

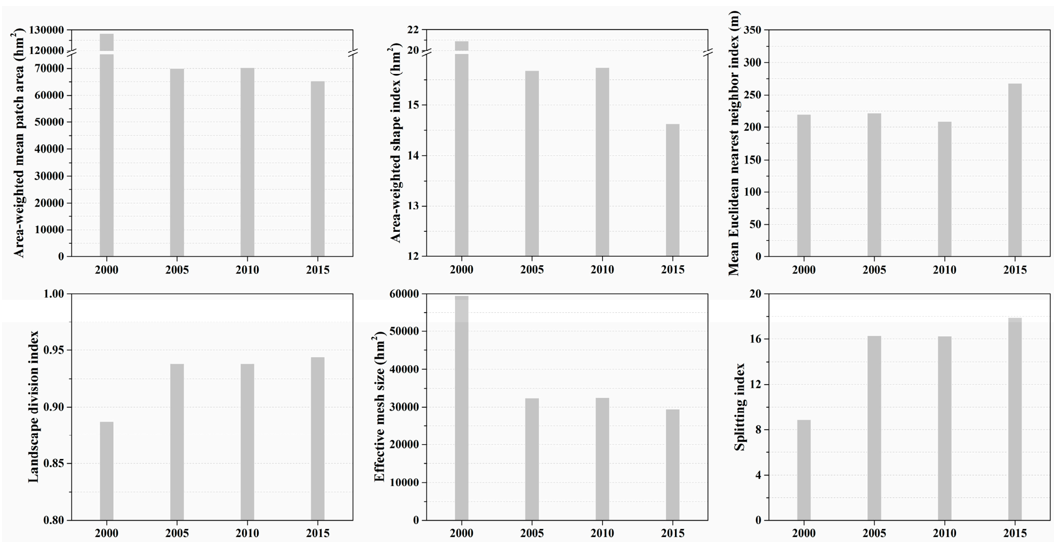

Figure 5. Forest fragmentation pattern in 2000, 2005, 2010, and 2015.

3.3. Forest Fragmentation Processes at Pixel Level

The distribution and dynamic changes of forest fragmentation processes in 2000–2005, 2005–2010, and 2010–2015 are shown in Figures 6–8, respectively. Shrinkage and subdivision processes were the dominant spatial processes during these three periods in the north of the study area; attrition became the main process from 2010–2015. According to the composition of forest areas converted into other land use types, more than 50.00% of the lost forest area was a result of shrinkage and subdivision, and forest land was replaced by cropland and urban land.

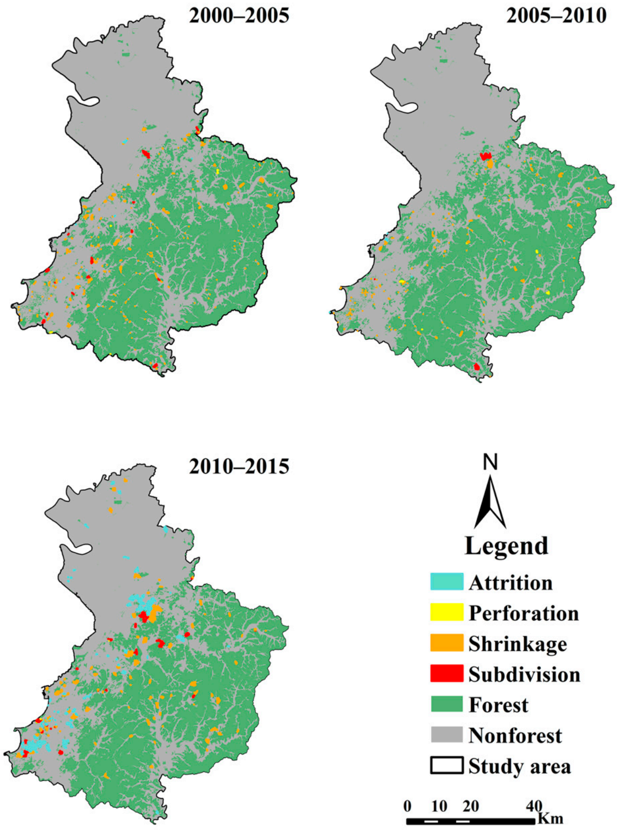

Figure 6. Distributions of forest fragmentation spatial processes in 2000–2005, 2005–2010, and 2010–2015.

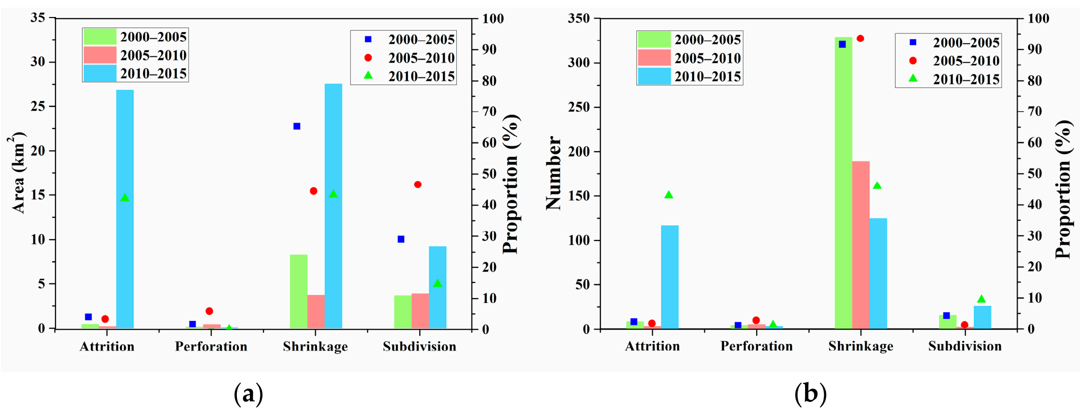

Figure 7. Area (**a**); and number (**b**) of different spatial processes in 2000–2005, 2005–2010, and 2010–2015.

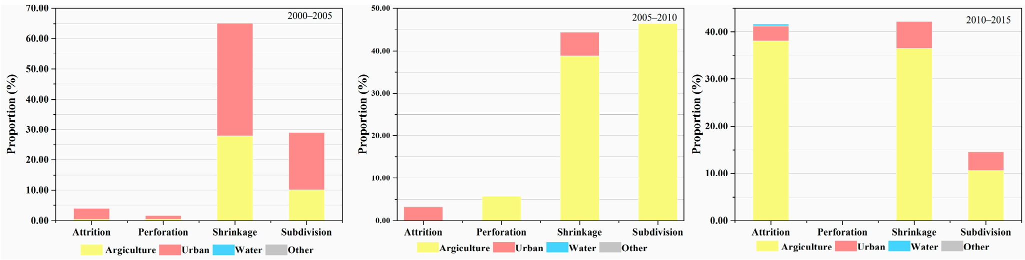

Figure 8. Percentages of forest land conversions into other land use types in different spatial processes in 2000–2005, 2005–2010, and 2010–2015.

3.4. Driving Factors of Forest Fragmentation

Figure 9 shows the global Moran's I coefficients of all forest fragmentation metrics at two different scales in four years. These values detected the spatial dependence within the neighborhood. In general, most of these coefficients were greater than zero at the two scales, indicating the commonly positive spatial autocorrelation in forest fragmentation in Yingkou region. Therefore, spatial scale effect and autocorrelation should be considered in the analysis of the driving factors of forest fragmentation.

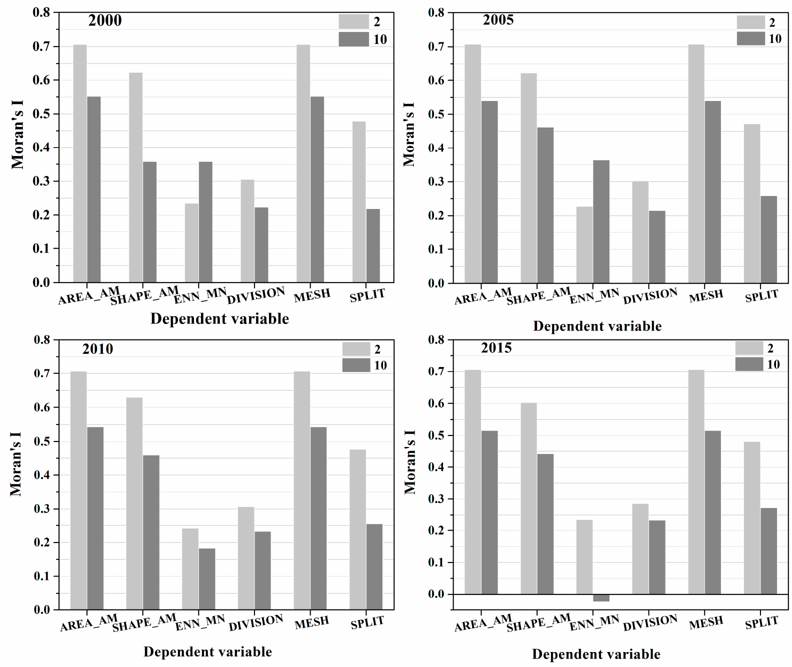

Figure 9. Spatial autocorrelation coefficients of the forest fragmentation metrics in 2000, 2005, 2010, and 2015 at 2 km scale and at 10 km scale.

All selected forest fragmentation metrics and determinants were introduced into the spatial error model and spatial lag model at two scales in four years. To better reflect the results of this study, Tables 3 and 4 show the suitable models (R^2 value greater than 0.45, and high Akaike info criterion value between two spatial models) and the coefficients of driving factors with a significant effect on forest fragmentation (p value less than 0.05). The results revealed that most of the models performed well; the change of area-weighted mean patch area, area-weighted shape index, and effective mesh size at the two scales was explained well by the models. The results also showed that spatial lag models were suitable for explaining the relationship between forest fragmentation and driving forces, especially at the 2 km scale. In addition, with increasing block scale, the changes in Euclidean nearest neighbor index were explained well by the spatial lag model in 2000 and 2015.

Table 3. Result of the spatial regression between forest fragmentation and the determinants at the 2 km scale (Only the suitable models ($R^2 \geq 0.45$; high AIC value between two spatial models) and significant factors ($p < 0.05$) are shown).

	Area-weighted mean patch area				**Area-weighted shape index**				**Effective mesh size**			
Variable	**2000 [b]**	**2005 [b]**	**2010 [b]**	**2015 [b]**	**2000 [b]**	**2005 [b]**	**2010 [b]**	**2015 [b]**	**2000 [b]**	**2005 [b]**	**2010 [b]**	**2015 [b]**
Constant						0.5262 **				−0.0087 *	−0.0086	
Elevation	−0.3928 **	−0.3654 **	−0.3674 **	−0.3693 **	−0.1877 **	−0.1917 **	−0.2214 **	−0.2293 **	−0.3928 **	−0.3654 **	−0.3674 **	−0.3693 **
Slope	0.4212 **	0.3938 **	0.3941 **	0.3977 **	0.2346 **	0.2535 **	0.2839 **	0.2844 **	0.4212 **	0.3938	0.3941 **	0.3977 **
Dis_C	0.5018 **	0.162412 *			1.5177 **	0.4749 **	0.7183 **	0.569 **	0.5015 **	0.1624 **		
Dis_T						−0.2069 **	−0.2501 **	−0.2641 **				
Dis_Rail				0.2945 **	−0.9118 **	1.047 **	1.673 **			0.3183 **		0.2945 **
Dis_H						−1.3239 **	−1.851 **					
Dis_N	0.0622 *					0.1542 **			0.0622 *			
Dis_P	−0.3725 **	−0.3016 **	−0.2760 **	−0.3388 **	−0.8173 **		−0.295 **	−0.3446 *	−0.3725 **		−0.276 **	−0.3388 **
Dis_X					−0.1735 **	−0.1798 **	−0.1764 **	−0.155 *				
Dis_Riv					0.1370 **	0.1661 **	0.2047 **	0.1599 *				
GDP			−0.0672 **	−0.0669 **	−0.0224	−0.0462 *	−0.1008 **	−0.1073 *	−0.0931 **	−0.0071 **	−0.0672 **	
W	0.6515	0.673	0.6669	0.6608	0.5851	0.6001	0.5804	0.5632	0.6515	0.673	0.6669	0.6608
R^2	0.6629	0.6577	0.6573	0.656	0.5731	0.5708	0.5818	0.5451	0.6629	0.6577	0.6573	0.656
AIC	2775.41	2813.89	2810.65	2811.97	3076.33	2654.41	3043.74	3156.4	2775.41	2813.89	2810.65	2811.97

* means $p < 0.05$, ** means $p < 0.01$ for the test. [b] means spatial lag model. Abbreviations: distance to city center (Dis_C), distance to towns (Dis_T), distance to railway (Dis_Rail), distance to highways (Dis_H), distance to national ways (Dis_N), distance to provincial ways (Dis_P), distance to county ways (Dis_X), distance to rivers (Dis_Riv), gross domestic product (GDP), *Wy* of spatial lag model (*W*), *R*-squared (R^2), and Akaike info criterion (AIC).

Table 4. Result of the spatial regression between forest fragmentation and the determinants at the 10 km scale (Only the suitable models ($R^2 \geq 0.45$; high AIC value between two spatial models) and significant factors ($p < 0.05$) are shown).

	Area-weighted mean patch area				**Area-weighted shape index**				**Effective mesh size**				**Mean Euclidean nearest neighbor index**	
Variable	**2000 [b]**	**2005 [a]**	**2010 [b]**	**2015 [b]**	**2000 [a]**	**2005 [a]**	**2010 [a]**	**2015 [b]**	**2000 [b]**	**2005 [a]**	**2010 [b]**	**2015 [b]**	**2000 [b]**	**2015 [b]**
Elevation		−1.6355 *		−1.6887 *		−2.4238 **	−2.7074 **	−2.8885 **		−1.6355 *	−1.6148 *	−1.6887 *		
Slope			1.5122 *	1.5466 *		1.9589 **	2.3185 **	2.4199 **			1.5122*	1.5465 *		
Dis_C	1.3107 *				2.4826 **	0.7326 *	0.6655 *		1.3107 *					
Dis_Rail				1.1288 **	−2.1986 **			0.8614 *				1.1288 **		
Dis_H					1.9233 *									
Dis_P	−0.9246 *	−0.6310 **	−0.7358 **	−0.8447 **	−1.4784 **	−0.5225 *	−0.7197 *	−0.6391 *	−0.9246 *	−0.631 **	−0.7358 **	−0.8447 **		
POP													0.5546 **	
GDP							−0.2442 *							0.2757 **
W/λ	0.4681	0.5402	0.5119	0.4378	0.3161	0.3334	0.2525	0.2282	0.4681	0.5402	0.5119	0.4378	0.4625	0.5633
R^2	0.5503	0.5458	0.5478	0.5114	0.4916	0.4863	0.4815	0.5089	0.5503	0.5458	0.5478	0.5114	0.5693	0.4742
AIC	185.82	186.82	187.549	191.239	189.655	190.724	190.171	187.806	185.826	186.82	187.549	191.239	182.419	194.925

* means $p < 0.05$, ** means $p < 0.01$ for the test. [a] means spatial error model, [b] means spatial lag model. Abbreviations: distance to city centers (Dis_C), distance to railway (Dis_Rail), distance to highways (Dis_H), distance to provincial ways (Dis_P), gross domestic product (GDP), Wy of spatial lag model (W), lambda of spatial error model (λ), *R*-squared (R^2), and Akaike info criterion (AIC).

The results in this study demonstrated that natural factors (e.g., elevation and slope), proximity factors (e.g., distance to city and distance to province roads), and socioeconomic factors (e.g., gross domestic product) significantly influence forest landscape fragmentation from a spatial perspective. These results also indicated that the determinants and their effects on forest fragmentation varied with scales and times. For example, gross domestic product significantly influenced the area of forest in 2010 and 2015 at 2 km scale, but had an insignificant impact in 2000 and 2005 at 2 km scale and in four years at 10 km scale.

4. Discussion

4.1. Forest Fragmentation and Land Use/Cover Change

Land use change is a local environmental issue and a force of global importance [39]. The transformation of natural land use by human activities may pose a severe threat to critical natural resources and ecosystem services [15], such as biological diversity [13], forest loss and fragmentation [40]. In Yingkou region, land use changes play an important role in forest fragmentation. Approximately 86.81 km^2 of forest was converted to urban land, cropland, water, or other land from 2000 to 2015 (Table 2). More than 80% of forests were converted to cropland during 2005–2010 and 2010–2015. These transitions may be due to the historical development of cropland in the study area and the needs of the growing human population. Despite the extensive transition from forest to cropland, considerable amounts of forest were transformed into urban areas because of the economic benefits of the urban landscape. Other land types were also converted to forest during these periods; the area and proportion of forest both increased because of the forest protection policy in 1998 and 1999 [30,31].

The analysis of pattern and processes of forest fragmentation indicated that forest fragmentation had become one of the main problems of land utilization in the study area. For example, at the landscape level (pattern), forest patches were more subdivided and isolated in the period of 2010–2015. At pixel level (processes), shrinkage and subdivision processes, which are the middle phases of landscape change [18], were the main forest fragmentation processes in all three time periods. Therefore, forest landscape fragmentation should be controlled both at pixel level and landscape level.

4.2. Driving Factors of Landscape Fragmentation

The relationship between landscape pattern changes and natural factors, spatial proximity factors, and socioeconomic factors was extensively studied in other regions [4,9,23]. In the present study, these factors also significantly influenced forest landscape fragmentation together from a spatial perspective at different scales, such as elevation, slope, distance to city, distance to province roads, and gross domestic product.

Elevation and slope are closely related to forest fragmentation, as explained by the probability of variations in forest fragmentation at 2 and 10 km block scales. The patches of forest were smaller on the gentle slopes, which is similar to the results in the study of Echeverria et al. (2008). Forests in gentle and low elevation area are always occupied by the expansion of agricultural and urban lands because of their low cost and greater benefits, whereas forests in steep and high elevation area are always protected to maintain region environment.

Distance to city center also influences the area, shape, and isolation of forest in this study and is caused by the distance decay effect of city development. This impact of city on forest fragmentation was also exhibited in Liu et al. (2014). When a forest is closer to the city centers, the forest is more isolated and has a higher possibility of being converted to agricultural or urban areas.

Road networks have been proven to segregate the forest landscape into smaller pieces and a greater number of patches [25]. This study showed that road networks had different influences on the forest at 2 and 10 km scales in Yingkou region. In particular, the distance to provincial ways had a greater impact on the area and shape of forests than other factors about roads, because of the strong effect and accessibility of provincial ways to neighboring forests.

Distance to rivers significantly influenced the shape of forests at the 2 km scale, indicating that forests would be regular near the rivers; this finding was consistent with the results of Gao and Liu (2012) and inconsistent with the results of Echeverria et al. (2008). This result is due to the fact that humans would tend to change the land use type around the water area to meet the water needs and other economic benefits in the study area, for example, the forests may be converted to cropland because of the need for sustenance.

Some studies demonstrated that landscape fragmentation was significantly influenced by socioeconomic changes and human demands, such as demographic conditions and economic dynamics [14,23]. In this study, increased gross domestic product would have an impact on the patterns of forest fragmentation, especially at the 2 km scale. Population significantly affected the isolation of forests only at the 10 km scale because of the scale effect of the forest fragmentation metrics. However, the forest was converted to other land use types, such as cropland and urban land, to meet the demands of growing production and population growth.

4.3. Recommendations for Forest Protection

As one of the dominant land use types, forests were reduced by 5.0 km^2 per year in 2000–2015 and became more isolated and subdivided in Yingkou region. Therefore, reasonable and effective measures to protect forest from fragmentation are urgently needed. On one hand, the management of land use change requires a multipronged method. For example, a long-term investigation of the forest should be conducted to identify its dynamic changes and analyze the change of landscape pattern and process from a spatial and temporal perspective. Hence, we can rationally utilize and scientifically manage forest resources, such as protecting the forest from being fragmented. On the other hand, several protective measures should be considered by the government, local communities, and public of the region, including the development of coordinated policies, enforcement of effective law, sustainable use of forest, integrated land-use planning, and adequate monitoring of land-use change [1]. For example, the subdivision process should be controlled and the atrition should be prohibited to protect forest resources in land use planning. In addition, the pattern of forest fragmentation should be considered in the land use planning, both the area of forest patches and the shape, isolation, and subdivision of forest patches that have not been considered in recent land use planning should be taken into account.

4.4. Limitations and Further Studies

Although this study assessed forest fragmentation and its determinants at different scales, there are still several limitations. First, the land use data used in this study were sourced from remote-sensing images and other institutions; however, the classification of images cannot be 100% correct, and the spatial misalignment of data may have resulted in incorrectly assessed pattern and processes of fragmentation [20]. Therefore, data processing is critical to reduce the misdetection of fragmentation. Second, the influence of the expansion of urban, roads, and rivers on forest fragmentation is limited to a certain distance [41]. The distance threshold of these factors on forest fragmentation should be further studied to determine detailed the relationship between urban growth and forest fragmentation. Third, the impact of climate on the ecosystem must be considered by using past data. Climate was not considered in this study, but this factor significantly influences forest fragmentation and loss [22,41,42].

5. Conclusions

This study successfully measured forest fragmentation at landscape and pixel levels from 2000 to 2015 in Yingkou region. Our results revealed that the forest landscape became more subdivided, isolated, and regular between 2010 and 2015 at the total forest landscape level. Results also showed that the dominant forest fragmentation processes were shrinkage and subdivision in the three time periods, and attrition became the main process from 2010 to 2015. Moreover, most forest patches in the three periods were replaced by urban growth and agricultural expansion. The methodology outlined in this contribution could also be used to evaluate landscape fragmentation for wetlands, croplands and other landscape types.

Spatial regression models were used to analyze the driving forces of forest landscape fragmentation in the study area. Our results revealed that elevation, slope, distance to city center, distance to province ways, and gross domestic product were the significant factors that influenced forest landscape fragmentation. This finding indicates that human activities were not the only significant driving factor of forest fragmentation. Natural factors, such as elevation and slope, also have a significant effect on forest fragmentation, and the effect should be further examined. This research provides valuable insights into the driving factors of forest fragmentation and several suggestions, such as the isolation and subdivision of forest patches should be controlled, to guide the pattern and processes of forest fragmentation.

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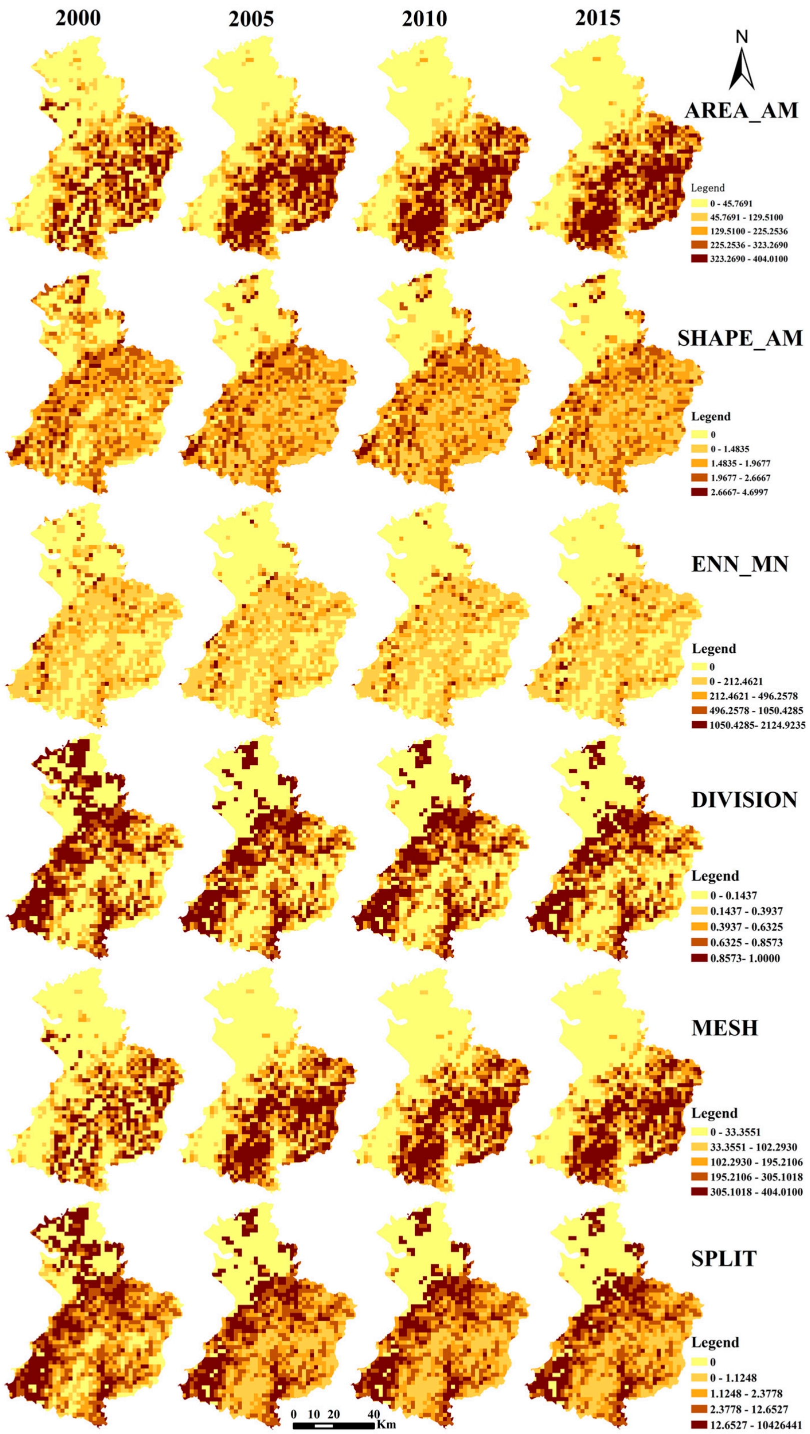
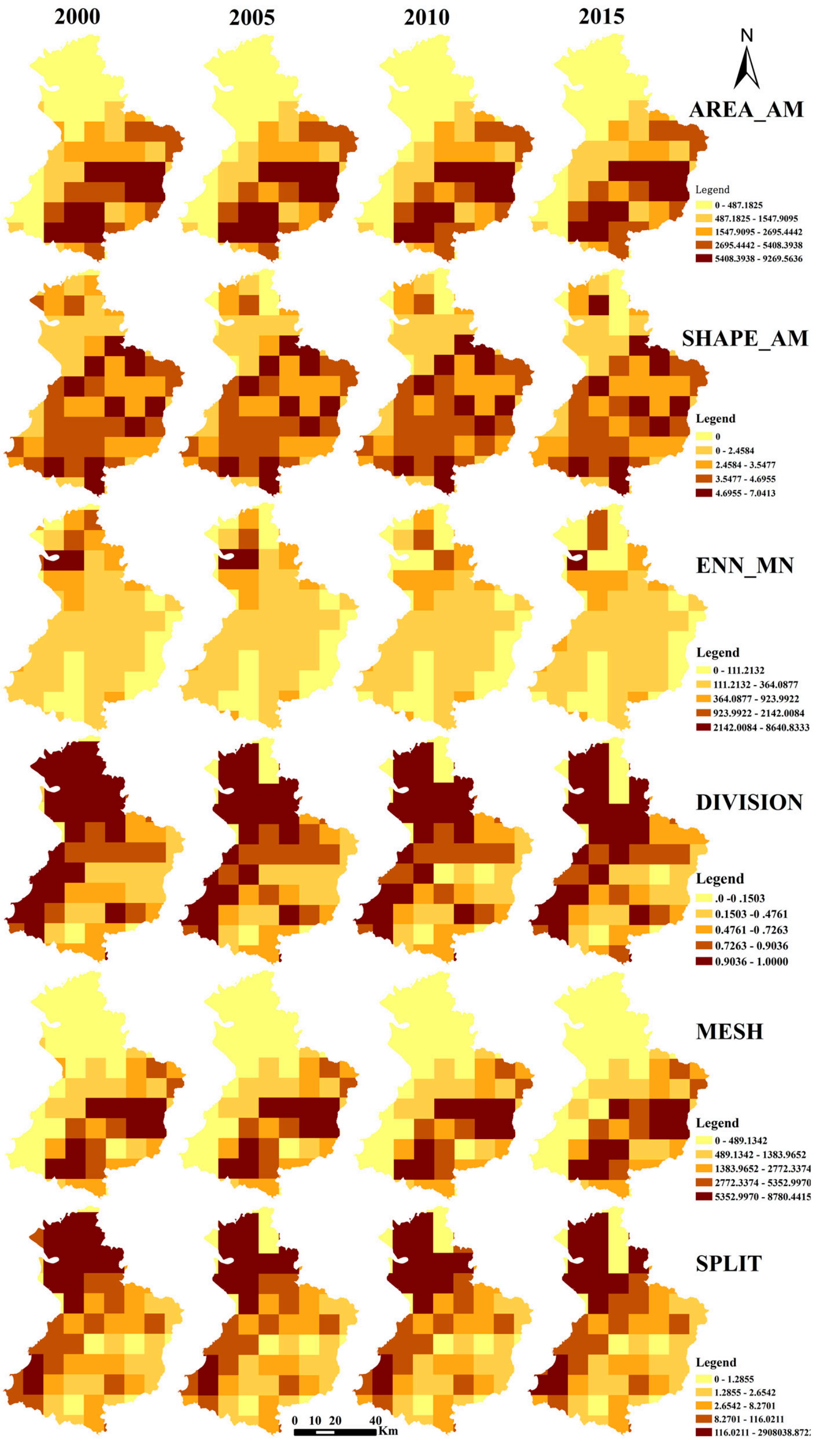
Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Distributions of Forest Fragmentation in 2000, 2005, 2010 and 2015 at 2 km Scale and 10 km Scale



(**a**)

Figure A1. *Cont.*



(**b**)

Figure A1. (**a**) Distributions of forest fragmentation in 2000, 2005, 2010 and 2015 at 2 km scale. (**b**) Distributions of forest fragmentation in 2000, 2005, 2010 and 2015 at 10 km scale.

References

1. FAO. *State of the World's Forests 2016: Forests and Agriculture—Land Use Challenges and Opportunities*; Food and Agriculture Organization of the United Nations: Rome, Italy, 2016.

2. Lele, N.; Joshi, P.K.; Agrawal, S.P. Assessing forest fragmentation in northeastern region (NER) of India using landscape matrices. *Ecol. Indic.* **2008**, *8*, 657–663. [CrossRef]
3. Wickham, J.D.; Riitters, K.H.; Wade, T.G.; Homer, C. Temporal change in fragmentation of continental US forests. *Landsc. Ecol.* **2008**, *23*, 891–898. [CrossRef]
4. Gao, J.; Liu, Y. Deforestation in Heilongjiang province of China, 1896–2000: Severity, spatiotemporal patterns and causes. *Appl. Geogr.* **2012**, *35*, 345–352. [CrossRef]
5. Fahrig, L. Effects of habitat fragmentation on biodiversity. *Annu. Rev. Ecol. Evol. Syst.* **2003**, *34*, 487–515. [CrossRef]
6. DeFries, R.S.; Asner, G.P.; Houghton, R. Trade-offs in land-use decisions: Towards a framework for assessing multiple ecosystem responses to land-use change. In *Ecosystems and Land Use Change*; American Geophysical Union: Washington, DC, USA, 2013; pp. 1–9.
7. Echeverria, C.; Coomes, D.A.; Hall, M.; Newton, A.C. Spatially explicit models to analyze forest loss and fragmentation between 1976 and 2020 in southern Chile. *Ecol. Model.* **2008**, *212*, 439–449. [CrossRef]
8. Saunders, D.A.; Hobbs, R.J.; Margules, C.R. Biological consequences of ecosystem fragmentation: A review. *Conserv. Biol.* **1991**, *5*, 18–32. [CrossRef]
9. Li, M.; Mao, L.; Zhou, C.; Vogelmann, J.E.; Zhu, Z. Comparing forest fragmentation and its drivers in China and the USA with Globcover v2.2. *J. Environ. Manag.* **2010**, *91*, 2572–2580. [CrossRef] [PubMed]
10. Li, H.; Franklin, J.F.; Swanson, F.J.; Spies, T.A. Developing alternative forest cutting patterns: A simulation approach. *Landsc. Ecol.* **1993**, *8*, 63–75. [CrossRef]
11. Franklin, J.F.; Forman, R.T.T. Creating landscape patterns by forest cutting: Ecological consequences and principles. *Landsc. Ecol.* **1987**, *1*, 5–18. [CrossRef]
12. Harris, L.D. *The Fragmented Forest: Island Biogeography Theory and the Preservation of Biotic Diversity*; University of Chicago Press: Chicago, IL, USA, 1984.
13. Collinge, S.K. Spatial arrangement of habitat patches and corridors: Clues from ecological field experiments. *Landsc. Urban Plan.* **1998**, *42*, 157–168. [CrossRef]
14. Liu, Y.; Feng, Y.; Zhao, Z.; Zhang, Q.; Su, S. Socioeconomic drivers of forest loss and fragmentation: A comparison between different land use planning schemes and policy implications. *Land Use Policy* **2016**, *54*, 58–68. [CrossRef]
15. Jaeger, J.A.G. Landscape division, splitting index, and effective mesh size: New measures of landscape fragmentation. *Landsc. Ecol.* **2000**, *15*, 115–130. [CrossRef]
16. Girvetz, E.H.; Thorne, J.H.; Berry, A.M.; Jaeger, J.A.G. Integration of landscape fragmentation analysis into regional planning: A statewide multi-scale case study from California, USA. *Landsc. Urban Plan.* **2008**, *86*, 205–218. [CrossRef]
17. Onojeghuo, A.O.; Blackburn, G.A. Forest transition in an ecologically important region: Patterns and causes for landscape dynamics in the Niger Delta. *Ecol. Indic.* **2011**, *11*, 1437–1446. [CrossRef]
18. Forman, R.T. *Land Mosaics: The Ecology of Landscapes and Regions*; Cambridge University Press: Cambridge, NY, USA, 1995.
19. Collinge, S.K.; Forman, R.T.T. A conceptual model of land conversion processes: Predictions and evidence from a microlandscape experiment with grassland insects. *Oikos* **1998**, *82*, 66–84. [CrossRef]
20. Li, S.; Yang, B. Introducing a new method for assessing spatially explicit processes of landscape fragmentation. *Ecol. Indic.* **2015**, *56*, 116–124. [CrossRef]
21. Riitters, K.; Wickham, J.; O'Neill, R.; Jones, B.; Smith, E. Global-scale patterns of forest fragmentation. *Conserv. Ecol.* **2000**, *4*, 3. [CrossRef]
22. Jiang, P.; Cheng, L.; Li, M.; Zhao, R.; Huang, Q. Analysis of landscape fragmentation processes and driving forces in wetlands in arid areas: A case study of the middle reaches of the Heihe River, China. *Ecol. Indic.* **2014**, *46*, 240–252. [CrossRef]
23. Gong, C.; Yu, S.; Joesting, H.; Chen, J. Determining socioeconomic drivers of urban forest fragmentation with historical remote sensing images. *Landsc. Urban Plan.* **2013**, *117*, 57–65. [CrossRef]
24. Su, S.; Wang, Y.; Luo, F.; Mai, G.; Pu, J. Peri-urban vegetated landscape pattern changes in relation to socioeconomic development. *Ecol. Indic.* **2014**, *46*, 477–486. [CrossRef]
25. Cai, X.; Wu, Z.; Cheng, J. Using kernel density estimation to assess the spatial pattern of road density and its impact on landscape fragmentation. *Int. J. Geogr. Inf. Sci.* **2013**, *27*, 222–230. [CrossRef]

26. Karlson, M.; Mörtberg, U. A spatial ecological assessment of fragmentation and disturbance effects of the Swedish road network. *Landsc. Urban Plan.* **2015**, *134*, 53–65. [CrossRef]
27. Forman, R.T.; Deblinger, R.D. The ecological road-effect zone of a Massachusetts (USA) suburban highway. *Conserv. Biol.* **2000**, *14*, 36–46. [CrossRef]
28. Liu, S.; Dong, Y.; Deng, L.; Liu, Q.; Zhao, H.; Dong, S. Forest fragmentation and landscape connectivity change associated with road network extension and city expansion: A case study in the Lancang River Valley. *Ecol. Indic.* **2014**, *36*, 160–168. [CrossRef]
29. Greenberg, J.A.; Kefauver, S.C.; Stimson, H.C.; Yeaton, C.J.; Ustin, S.L. Survival analysis of a neotropical rainforest using multitemporal satellite imagery. *Remote Sens. Environ.* **2005**, *96*, 202–211. [CrossRef]
30. Yu, D.; Zhou, L.; Zhou, W.; Ding, H.; Wang, Q.; Wang, Y.; Wu, X.; Dai, L. Forest management in Northeast China: History, problems, and challenges. *Environ. Manag.* **2011**, *48*, 1122–1135. [CrossRef] [PubMed]
31. Van Den Hoek, J.; Ozdogan, M.; Burnicki, A.; Zhu, A.X. Evaluating forest policy implementation effectiveness with a cross-scale remote sensing analysis in a priority conservation area of Southwest China. *Appl. Geogr.* **2014**, *47*, 177–189. [CrossRef]
32. The Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Sciences. Available online: http://www.gscloud.cn (accessed on 2 March 2017).
33. Zhang, Z.; Li, A.; Lei, G.; Bian, J.; Wu, B. Change detection of remote sensing images based on multiscale segmentation and decision tree algorithm over mountainous area: A case study in Panxi region, Sichuan Province. *Acta Ecol. Sin.* **2014**, *34*, 7222–7232.
34. Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences. Available online: http://www.resdc.cn (accessed on 2 March 2017).
35. Anselin, L. *Exploring Spatial Data with GeoDa: A Workbook*; Center for Spatially Integrated Social Science: Santa Barbara, CA, USA, 2005.
36. Tan, R.; Liu, Y.; Liu, Y.; He, Q.; Ming, L.; Tang, S. Urban growth and its determinants across the Wuhan urban agglomeration, central China. *Habitat Int.* **2014**, *44*, 268–281. [CrossRef]
37. Anselin, L. *Spatial Econometrics: Methods and Models*; Kluwer Academic Publishers: London, UK, 1988; pp. 310–330.
38. Ye, X.; Wu, L. Analyzing the dynamics of homicide patterns in Chicago: ESDA and spatial panel approaches. *Appl. Geogr.* **2011**, *31*, 800–807. [CrossRef]
39. Foley, J.A.; DeFries, R.; Asner, G.P.; Barford, C.; Bonan, G.; Carpenter, S.R.; Chapin, F.S.; Coe, M.T.; Daily, G.C.; Gibbs, H.K.; et al. Global consequences of land use. *Science* **2005**, *309*, 570–574. [CrossRef] [PubMed]
40. Abdullah, S.A.; Nakagoshi, N. Forest fragmentation and its correlation to human land use change in the state of Selangor, peninsular Malaysia. *For. Ecol. Manag.* **2007**, *241*, 39–48. [CrossRef]
41. Fuller, D.O. Forest fragmentation in Loudoun County, Virginia, USA evaluated with multitemporal Landsat imagery. *Landsc. Ecol.* **2001**, *16*, 627–642. [CrossRef]
42. Jin, J.; Wang, Y.; Jiang, H.; Cheng, M. Recent NDVI-based variation in growth of Boreal intact forest landscapes and its correlation with climatic variables. *Sustainability* **2016**, *8*, 326. [CrossRef]