

Article

Analysis of the Drivers of Landscape Fragmentation in Hainan Tropical Rainforest National Park Using XGBoost-SHAP

Yuanling Li ^{1,2,†}, Yuexin Jiang ^{1,2,†}, Xiaohua Chen ^{1,2}, Tingtian Wu ^{1,2}, Xiaoyan Pan ^{1,2}, Guangyang Li ^{1,2} and Zongzhu Chen ^{1,2,*}

¹ Hainan Academy of Forestry (Hainan Academy of Mangrove), Haikou 571100, China; liyuanlinghn@163.com (Y.L.); jiangyx0331@163.com (Y.J.); xiaohua.chen@hnaf.ac.cn (X.C.); tingtian.wu@hnaf.ac.cn (T.W.); panxiaoyan@hnaf.ac.cn (X.P.); li15130574839@163.com (G.L.)

² Key Laboratory of Tropical Forestry Resources Monitoring and Application of Hainan Province, Haikou 571100, China

* Correspondence: chenzongzhu@foxmail.com

[†] These authors contributed equally to this work.

Abstract

Hainan Tropical Rainforest National Park is a prime example of a “continental island” tropical rainforest and holds significant value for biodiversity conservation. However, human activities have led to frequent changes in land use and increased habitat fragmentation within the park; a precise analysis of the underlying mechanisms is necessary for ecological restoration. Consequently, drawing upon land-use data from 2000 to 2020, this study coupled multi-dimensional fragmentation metrics (CFI, AFI, and SFI) with the XGBoost-SHAP framework to systematically unravel the spatiotemporal dynamics and underlying driving mechanisms of landscape fragmentation in Hainan Tropical Rainforest National Park. Our findings revealed that the spatial configuration of fragmentation predominantly propagated along river networks and transport corridors, accompanied by a fluctuating ‘decline–rise–decline’ temporal trajectory. Notably, the XGBoost-SHAP attribution highlighted a distinct temporal shift in the dominant drivers: fragmentation was primarily mitigated (negatively driven) by NDVI between 2000 and 2010 but was subsequently exacerbated (positively driven) by GDP growth from 2010 to 2020. The findings of this study provide data support and a scientific basis for ecosystem restoration and land use planning in Hainan Tropical Rainforest National Park.

Keywords: landscape fragmentation; driving force Hainan; Tropical Rainforest National Park; XGBoost-SHAP; ecological restoration



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1. Introduction

The precipitous decline in global biodiversity is largely driven by the destruction and degradation of natural ecosystems, especially forests [1]. This habitat destruction involves not merely total area loss, but also profound landscape fragmentation. To isolate the effects of altered spatial configurations, classical landscape ecology strictly defines landscape fragmentation (i.e., *fragmentation per se*) as the subdivision of large, contiguous patches into smaller, isolated fragments, independent of habitat loss [2]. Altered regional landscape patterns, heightened patch isolation, and anthropogenic edge disturbances synergistically induce long-term structural and functional shifts within the remaining patches [1,3]. Notably, fragmentation-induced edge effects have become a critical microenvironmental driver for increased tree mortality [4]. Under the strategy of China’s Ecological Civilization, the

optimization of territorial space and ecological conservation have been elevated to unprecedented importance. Consequently, analyzing the drivers of landscape fragmentation serves as a crucial foundation for scientific management and effective policy regulation. Particularly against the backdrop of increasing habitat loss and fragmentation, China is actively advancing the development of a system of protected areas centered on national parks, effectively preserving the authenticity and integrity of ecosystems [5]. Striking the right balance between conservation goals in protected areas and development in surrounding areas to improve human well-being is a central social issue [6]. Therefore, identifying and quantifying the key drivers of land use change in national parks is essential for the more rational and effective management of these parks. Against this backdrop, unraveling the driving mechanisms of landscape fragmentation serves not merely as a vital avenue for reconciling conservation-development conflicts but as an essential prerequisite for evidence-based spatial management, effective policy interventions, and sustainable forest management.

Landscape fragmentation is generally driven by the complex interplay between environmental and anthropogenic factors, with its underlying mechanisms exhibiting pronounced regional heterogeneity. In the Amazon basin, fragmentation is primarily fueled by persistent deforestation, land-use conversions, and mounting demographic pressures [4]. Across Southeast Asia, economic land concessions in Cambodia have precipitated intensive logging, posing a direct threat to the integrity of core forests [7], whereas agricultural expansion remains the dominant driver in northern Thailand [8]. Conversely, in China, macro-level ecological restoration initiatives aimed at mitigating habitat degradation and fragmentation—such as desertification control and the Grain for Green Program—have substantially facilitated vegetation recovery and the transition of non-forested areas back into woodlands [9]. However, within the framework of a protected area system centered on national parks, although policies strictly restrict resource extraction and agricultural development, conflicts persist because of the overlap between community development and ecological conservation. Human activities, such as infrastructure development, urban sprawl, and shifts in livelihoods, remain key drivers of land use changes in protected areas, and these human disturbances are even spreading into core protected areas [10,11]. These natural, policy, and socioeconomic factors collectively contribute to the ongoing evolution of land use patterns [12,13], which in turn profoundly affects the spatial pattern of the forest landscape.

Analytical methods for identifying the drivers of land use change have advanced significantly and have become key strategies for ecological planning and restoration.

Current research primarily employs statistical and machine learning methods to conduct quantitative analyses of the drivers of land use change. These methods include principal component analysis, random forest analysis, logistic regression, Geodetector, multiple linear regression (MLR), geographically weighted regression (GWR), and the XGBoost-SHAP model [14]. Different models have their own advantages, but they also have limitations [13]. While traditional MLR intuitively reveals the marginal effects of individual variables, its strict linear assumptions hinder its ability to capture complex non-linear relationships and interactions among variables [15]. Geodetector excels at analyzing factor interactions; however, it requires the discretization of continuous variables, inevitably leading to a loss of original data information [16]. Recently, machine learning models (e.g., neural networks and Random Forests) have been widely adopted due to their exceptional non-linear analytical capabilities, yet they possess inherent limitations. For instance, neural networks are highly susceptible to overfitting, while Random Forests exhibit a limited upper bound in accuracy when extracting deeply complex patterns [13]. To further enhance model accuracy and generalization performance, current research trends

have shifted towards more advanced machine learning algorithms, such as LightGBM [17], CatBoost [18], and XGBoost. Among these, XGBoost has been extensively applied in studies on land use and forest cover evolution, owing to its robust non-linear fitting capabilities, efficient feature selection mechanism, and superior resistance to overfitting [19]. Nevertheless, the “black-box” nature of advanced algorithms like XGBoost obscures in-depth mechanistic interpretations of the underlying driving forces. Consequently, introducing the SHAP (SHapley Additive exPlanations) post hoc explanation framework has emerged as a crucial solution to overcome this barrier [20]. This framework not only renders the non-linear decision-making process completely transparent but also precisely quantifies feature contributions from global, local, and even spatial multidimensional perspectives, thereby significantly enhancing the interpretability and applicability of machine learning under complex geographical conditions [20,21]. Particularly in landscape ecological assessments, the XGBoost-SHAP model can not only accurately identify the complex non-linear response patterns of driving factors but also scientifically detect critical ecological mutation thresholds that trigger landscape fragmentation [22], thereby providing a reliable quantitative basis for habitat conservation decision-making.

Hainan Tropical Rainforest National Park (HNTRNP) is home to China’s most concentrated, best-preserved, and largest contiguous expanse of “continental island” tropical rainforest, which serves as a repository for globally unique flora, fauna, and genetic resources [23,24]. However, in the mid-to-late 20th century, large-scale industrial logging and slash-and-burn farming reduced the area of natural forests to less than 1400 km², accounting for only 10.42% of the total land area. Forest fragmentation is worsening, posing a serious threat to wildlife habitats. In recent years, driven by policies related to the Hainan Free Trade Port and the International Tourism Island, infrastructure development within HNTRNP has increased. While this has generated economic benefits, it has also led to a reduction in habitats within the national park, increased landscape fragmentation, and disrupted wildlife migration routes [25].

Against this backdrop, the overarching objective of this study is to comprehensively assess the spatiotemporal dynamics of landscape fragmentation in Hainan Tropical Rainforest National Park and to unravel its complex underlying driving mechanisms. To achieve this, we outline two primary tasks: (1) quantitatively evaluating land-use dynamics and the evolution of spatial landscape configurations from 2000 to 2020 using a composite suite of landscape metrics; and (2) introducing the XGBoost-SHAP framework to elucidate the relative contributions of biophysical, socio-economic, and policy factors to fragmentation. This research carries substantial methodological and practical significance. Methodologically, by integrating composite landscape metrics with the SHAP-interpreted XGBoost model, we transcend the limitations of traditional linear models in capturing complex non-linear ecological processes, thereby allowing for the precise quantification of the localized contributions of various drivers. Practically, this study will yield spatially explicit maps of driver importance alongside robust quantitative assessments. These deliverables will not only offer direct empirical evidence for optimizing territorial spatial planning within the national park but also precisely inform spatially differentiated ecosystem restoration strategies, ultimately fostering a sustainable balance between strict rainforest conservation and local community development.

2. Materials and Methods

2.1. Study Area

HNTRNP (108°44′32″ E–110°04′43″ E, 18°33′16″ N–19°14′16″ N) [24], which is located in the mountainous region of central Hainan Island, spans nine cities and counties, including Wuzhishan, Qiongzong, and Baisha, with a total area of approximately 4269 km² [26],

accounting for approximately 12.1% of Hainan Island’s land area (Figure 1). The national park covers a wide range of elevations, with the highest point at Wuzhishan (1867 m) and the lowest at the Duzong River Valley in the Diaoluo Mountain area (45 m). The study area is characterized by a tropical maritime monsoon climate, with an annual mean temperature ranging from 22.5 °C to 26.0 °C and a long-term average annual precipitation of 1759 mm. Precipitation is unevenly distributed throughout the year, with distinct dry and wet seasons. The favorable climate has fostered a high level of biodiversity, with 3653 species of vascular plants and 540 species of terrestrial vertebrates recorded [5,26].

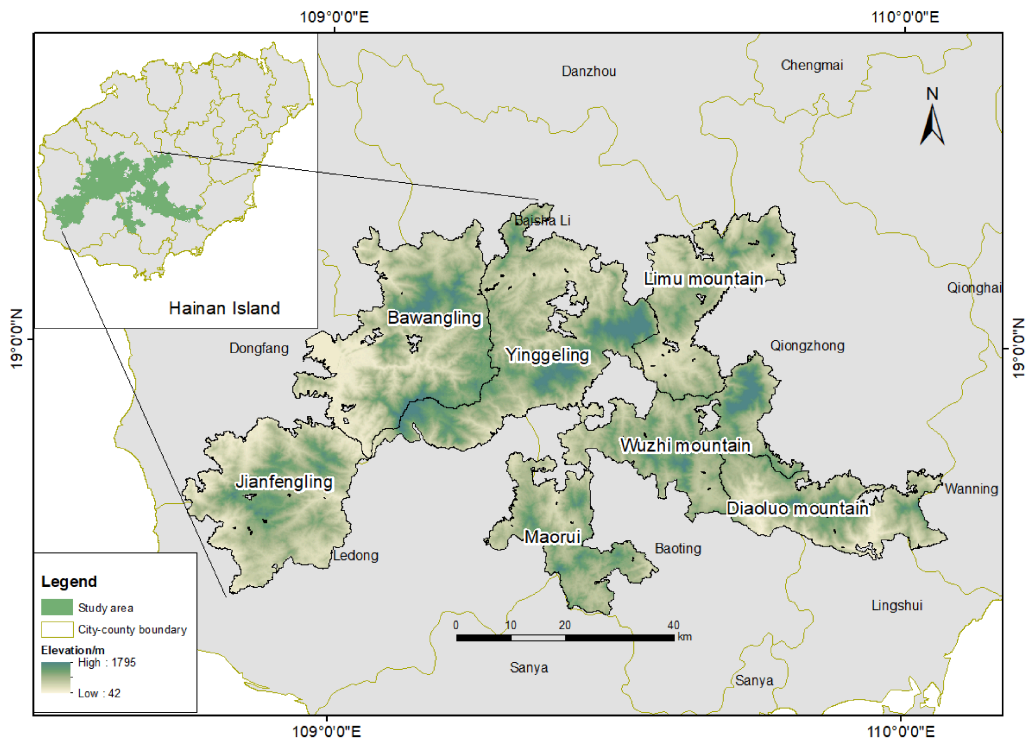


Figure 1. Location of the study area.

2.2. Data Sources and Preprocessing

The data used in this study include land use data, topographic data, meteorological data, aboveground biomass data, and socioeconomic data (Table 1). All the data were resampled to a spatial resolution of 30 m and projected using the CGCS2000_3_Degree_GK_CM_111E coordinate system.

Table 1. Description of data sources and processing methods.

Type	Year	Resolution	Data Sources and Processing
Land Use/Cover Change (LUCC) Data	2000, 2005, 2010, 2015, 2020	30 m	The data are derived from the China LUCC dataset developed by Xu et al. [27], which is available through the Resource and Environmental Science Data Registration and Publication System (http://www.resdc.cn/DOI , accessed on 3 June 2026). It has a spatial resolution of 30 m and uses the Krasovsky 1940 Albers coordinate system. Based on the natural attributes of land resources, a two-tier classification system is employed, covering six major categories and 25 subcategories, including land use/land cover types such as Paddy field, Dryland, Forest land, and Shrub forest.

Table 1. Cont.

Type	Year	Resolution	Data Sources and Processing
Meteorological data	2000, 2005, 2010, 2015, 2020	1 km	It mainly includes the annual average temperature and annual average precipitation, with data sourced from the Resource and Environment Data Cloud Platform, Chinese Academy of Sciences (http://www.resdc.cn , accessed on 3 June 2026).
Digital Elevation Model (DEM)	2019	30 m	The 30 m resolution ASTER GDEM digital elevation data is sourced from the Geospatial Data Cloud (https://www.gscloud.cn/ , accessed on 3 June 2026), and slope and aspect data are extracted from the elevation data using the Surface Analysis tools in ArcGIS 10.8 software.
NDVI	2000, 2005, 2010, 2015, 2020	1 km	The data were obtained from the China Annual NDVI and EVI 1 km dataset developed by Xu [28], available at the Resource and Environmental Science Data Registration and Publishing System (http://www.resdc.cn , accessed on 3 June 2026).
Socioeconomic data	2000, 2005, 2010, 2015, 2020	1 km	All data are sourced from the Resource and Environment Science Data Registration and Publication System; among them, the GDP data is from Xu [29]; population data from Fu et al. [30]; and nighttime light data from Xu [31] (http://www.resdc.cn , accessed on 3 June 2026).
Aboveground Biomass (AGB)	2000, 2005, 2010, 2015, 2020	30 m	Changes in forest carbon stocks have a significant impact on LUCC [32], and AGB is a key indicator of carbon stocks. The data are sourced from the annual Chinese forest AGB dataset developed by Cai et al. [33] using multispectral remote sensing data and a residual neural network, with a spatial resolution of 30 m and the WGS84 coordinate system.
Human Footprint	2000, 2005, 2010, 2015, 2020	1 km	The data is sourced from the global annual human footprint dataset developed by Mu et al. [34], with a spatial resolution of 1 km and in the WGS84 coordinate system. (https://doi.org/10.6084/m9.figshare.16571064 , accessed on 3 June 2026)
HNTRNP Boundary Data	-	-	Data sourced from the official website of the Hainan Bureau of Surveying, Mapping and Geoinformation (https://hism.mnr.gov.cn/sjxf/ , accessed on 3 June 2026).

To address the differences in spatial and temporal resolution among multisource datasets, this study adopted the approach described in previous research [35]: (1) In the analysis of driving factors, to standardize spatial resolution, all factors with a resolution greater than 1000 m were resampled to 30 m using the resampling method. (2) In terms of the time period, the meteorological, AGB, and socioeconomic data cover the period from 2000 to 2020, which is consistent with the study's time series. Furthermore, the DEM data exhibit high temporal stability and require no processing.

2.3. Research Methods

This study consists of four main parts: (1) Data collection and preprocessing. (2) Analysis of land use changes. Using a land use transition matrix, this study analyzed the patterns and trends of land use transitions within HNTRNP from 2000 to 2020. (3) Extraction of

landscape indices. In this study, the moving window method was employed, and LULC data from HNTRNP were used to select nine landscape indices. These indices were integrated into three composite indices based on patch connectivity, aggregation, and structure to quantitatively analyze the spatial patterns of land use change [36]. (4) Driver analysis method. XGBoost-SHAP was selected to analyze the drivers of land use. The types of drivers included topography, meteorology, AGB, environment, and socioeconomic factors.

2.3.1. Analysis of Land Use Change

The land use transition matrix enables a quantitative analysis of the area and direction of transitions between different land use types across various time periods, revealing the patterns and trends of transitions within and between land use types [37,38]. The formula is as follows:

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

where S represents the land use transition matrix; n represents the number of land types; i and j denote land types at the beginning and end of the study period, respectively, with i and $j = 1, 2, 3, \dots, n$; and S_{ij} represents the area that has transitioned from type i to type j .

2.3.2. Landscape Pattern Analysis Method

Landscape indices effectively reflect the spatial configuration characteristics of landscape structure and landscape pattern [39,40]. On the basis of land use/land cover maps, this study used Fragstats 4.2 software to extract nine landscape indices from within the national park using a moving window approach and analyzed their connectivity, aggregation, and structure. Zou et al. [36] proposed a set of quantitative forest fragmentation indices: the connectivity-based fragmentation index (CFI), the aggregation-based fragmentation index (AFI), and the structure-based fragmentation index (SFI). The CFI includes the total core forest area (TCA), largest patch index (LPI), and landscape fragmentation index (LDI). The higher the CFI value is, the stronger the connectivity and the higher the degree of clustering. The AFI includes the aggregation index (AI), percentage of similar adjacencies (PLADJ), and the average Euclidean nearest-neighbor distance between patches (ENN). The higher the AFI value is, the higher the degree of aggregation. The SFI includes the mean patch area (MPA), edge density (ED), and number of patches (NP). A higher SFI value indicates a greater degree of fragmentation.

This study employed semivariogram analysis—a fundamental geostatistical technique—to quantitatively characterize spatial heterogeneity [41]. By integrating the moving window method with semivariogram analysis based on 30 m resolution land-use data, we systematically evaluated seven distinct spatial scales (from 300 m to 2100 m, with a 300 m increment). Specifically, nine fundamental landscape metrics were first extracted utilizing Fragstats 4.2, which were then processed in ArcGIS 10.8 to generate spatial raster maps for three composite landscape indices. Based on a comprehensive assessment of the model goodness-of-fit (R^2) and spatial autocorrelation structures across varying scales, the 300 m window was identified as the optimal analytical scale for subsequent analyses (Table S1).

$$CFI = \frac{LDI_{nor} + TCA_{nor} + LPI_{nor}}{3}$$

$$AFI = \frac{ENN_{nor} + PLADJ_{nor} + AI_{nor}}{3}$$

$$SFI = \frac{ED_{nor} + NP_{nor} + MPA_{nor}}{3}$$

where LDI_{nor} , TCA_{nor} , LPI_{nor} , ENN_{nor} , $PLADJ_{nor}$, AI_{nor} , ED_{nor} , NP_{nor} , and MPA_{nor} represent the normalized values of the respective fragmentation metrics.

2.3.3. Driving Force Analysis

To quantify the relative contributions of diverse drivers to landscape fragmentation within HNTRNP, we employed the eXtreme Gradient Boosting (XGBoost) algorithm to decipher complex ecological relationships in large-scale datasets. By constructing an ensemble of decision trees, XGBoost utilizes a forward stagewise additive approach to iteratively fit residuals [42], making it exceptionally capable of capturing the complex, non-linear dynamics of drivers during long-term landscape evolution. To circumvent the inherent ‘black-box’ limitations of traditional machine learning models, we further coupled XGBoost with the SHAP (SHapley Additive exPlanations) framework, an interpretability tool derived from cooperative game theory [43]. By computing the marginal contribution of individual features to the overall model prediction, the SHAP method facilitates the precise identification and quantification of the paramount drivers dictating landscape fragmentation in HNTRNP. Furthermore, it enables the intuitive visualization of individual factor response patterns, effectively illuminating the critical elements that exert the most profound influence [42].

To systematically explore the underlying driving forces (Table 2), a spatial grid (fishnet) with a 1 km × 1 km resolution was constructed via ArcGIS 10.8, extracting a total of 3308 effective sampling points within the study area. The model hyperparameters were set as follows: max_depth = 3, learning_rate = 0.05, n_estimators = 100, random_state = 42, colsample_bytree = 0.8.

Table 2. Performance metrics of the XGBoost model for predicting AFI, CFI, SFI.

Composite Landscape Fragmentation Index	Year	R^2	RMSE	MAPE (%)
AFI	2005	0.273	0.063	7.534
	2010	0.251	0.069	8.467
	2015	0.216	0.066	8.063
	2020	0.255	0.061	7.686
CFI	2005	0.007	0.127	7.623
	2010	0.006	0.134	9.423
	2015	0.005	0.131	9.238
	2020	0.007	0.134	8.327
SFI	2005	0.005	0.133	8.017
	2010	0.001	0.136	8.928
	2015	0.004	0.139	9.008
	2020	0.004	0.147	8.453

In the driving force analysis, the absolute AFI value derived from the moving window analysis was selected as the dependent variable (e.g., the 2000–2005 stage corresponds to the AFI in 2005). Table 3 shows extremely poor fits for CFI and SFI. Only AFI demonstrates valid explanatory power ($R^2 > 0.2$) with the lowest and most stable prediction errors (RMSE, MAPE), justifying its selection for the subsequent driving force analysis. On the basis of previous studies [32,44,45], we selected 11 driving factors, namely, the DEM, slope, aspect, annual mean temperature (Tem), annual mean precipitation (Pre), NDVI, annual aboveground biomass (AGB), population density, GDP per capita, and human footprint. We also tested the driving factors for multicollinearity by calculating the variance inflation

factor (VIF) and removing those with high VIF values (>10), which indicate the presence of multicollinearity [42]. For Nighttime Light, the p -values were consistently >0.05 across the models for 2005, 2010, 2015, and 2020.

Table 3. Variance Inflation Factor (VIF) and significance analysis of the explanatory variables incorporated in the XGBoost model.

Driving Factors	2005		2010		2015		2020	
	p	VIF	p	VIF	p	VIF	p	VIF
Aspect	0.01	1.01	<0.01	1.01	<0.01	1.01	<0.01	1.01
Slope	0.04	1.10	0.03	1.10	0.03	1.10	0.01	1.12
DEM	0.02	3.06	0.03	3.03	0.03	3.03	0.04	4.13
Temperature	0.01	5.42	0.10	3.56	0.05	3.56	0.05	5.10
Precipitation	0.03	3.68	0.05	1.68	0.04	1.68	0.01	2.12
NDVI	0.02	1.20	<0.01	1.17	<0.01	1.17	0.05	1.11
Aboveground Biomass	<0.01	1.08	0.03	1.11	0.03	1.11	0.01	1.10
GDP	0.03	1.09	0.05	1.17	0.05	1.17	0.04	1.29
Human Footprint	<0.01	1.19	<0.01	1.16	<0.01	1.16	<0.01	1.16
Nighttime Light	0.80	1.01	0.53	1.04	0.53	1.04	0.98	1.06
Population Density	0.05	1.00	0.02	1.00	0.02	1.00	<0.01	1.01

3. Results

3.1. Characteristics of Spatial Pattern Dynamics in the Hainan Tropical Rainforest National Park Ecosystem

3.1.1. Changes in the Spatial Patterns of Land Use Types

From a temporal perspective (Figure 2), between 2000 and 2020, HNTRNP consistently maintained a forest-dominated landscape, with forest cover remaining above 80%. During the study period, the forest area fluctuated but increased slightly overall, following a pattern of “initial growth followed by decline.” Ultimately, the forest area increased by 24.34 km², reaching a peak of 3640.03 km² in 2005. Grasslands with high coverage are the second-largest land use type; their area followed a pattern of “initial increase followed by a decline” before gradually stabilizing, with a net decrease of 25.66 km² during the study period.

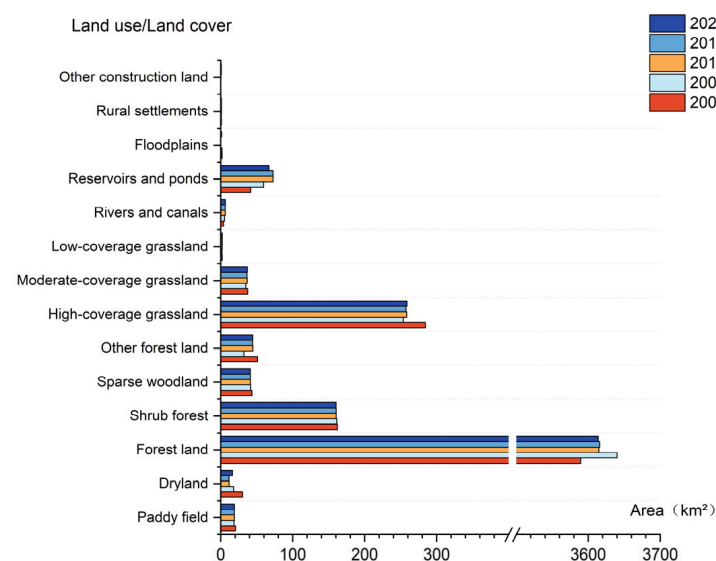


Figure 2. LUCC area in Hainan Tropical Rainforest National Park, 2000–2020.

Although the size of the shrubland has decreased slightly, it has remained generally stable. During the study period, the expansion of reservoirs and ponds was most significant, with their total area increasing by 25.51 km². In contrast, tidal flats, rural settlements, and other developed land accounted for less than 0.1% of the total area during the study period. Overall, the land use structure in the study area exhibited a high degree of stability during the study period.

From a spatial perspective (Figure 3), changes in land use patterns within HNTRNP between 2000 and 2020 exhibited marked spatial heterogeneity, which was primarily concentrated around waterways and roads. Specifically, as exemplified by the areas where Limu Mountain and Wuzhi Mountain meet, the changes involve the conversion of grasslands with high vegetation cover into forested areas, as well as the conversion of other nonforested areas into forested areas. Another region exhibiting large changes is the southern part of Bawangling, where dry land and grasslands with high vegetation cover have been converted into reservoirs and ponds. Apart from the areas mentioned above, spatial changes in other land categories have been relatively sporadic and have not formed any significant trends.

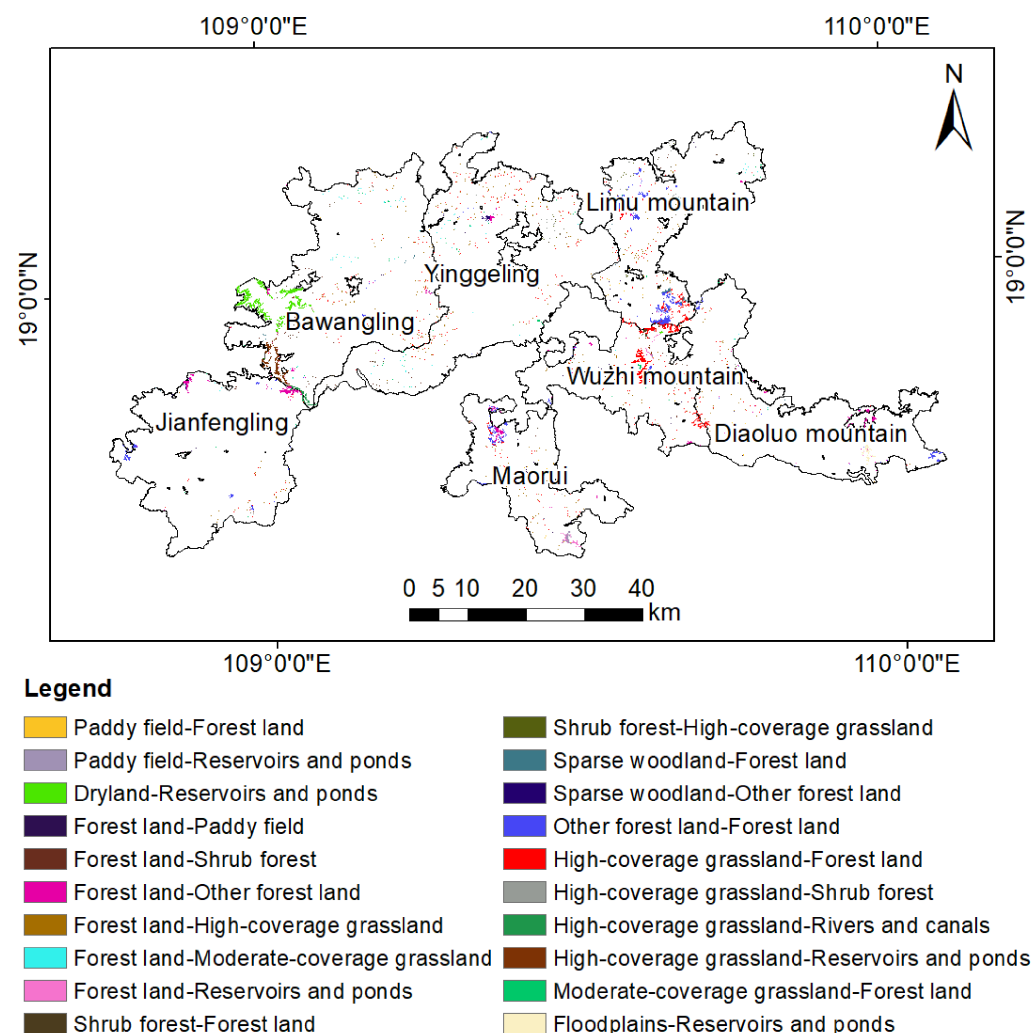


Figure 3. Land use change map. (Change patches smaller than 1 km² are omitted for visual clarity).

3.1.2. Land Use Transition Matrix

Land use changes in HNTRNP remained relatively stable from 2000 to 2020 (Figure 4), with a total land use change of 122.35 km². Overall, the shift was primarily from high-coverage grassland and other forestland to forestland. High-coverage grassland and

other forestland were reclassified as forestland, with areas of 27.11 km² and 18.68 km², respectively. Dry land was reclassified as rivers and canals, with a total area of 13.73 km².

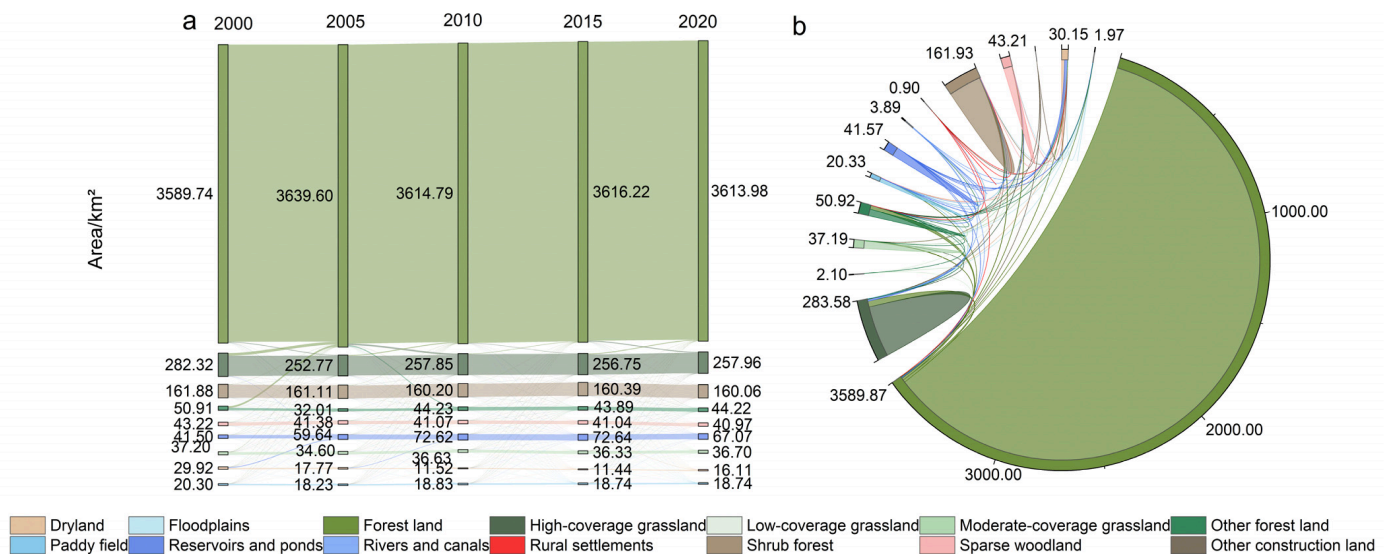


Figure 4. Land use change (a) is a Sankey diagram showing changes in land use types for 2000, 2005, 2010, 2015, and 2020; (b) is a chord diagram showing the transfer quantities between 2000 and 2020. In the Sankey diagram, transition flows smaller than 10 km² are omitted for visual clarity.

From 2000 to 2010, there was a significant conversion of drylands to reservoirs and ponds, covering an area of 17.48 km². Other forestland and high-coverage grassland also revealed substantial changes, with forest conversion areas of 18.43 km² and 21.73 km², respectively. From 2010 to 2020, land use changes remained relatively stable. The primary land use change involved the conversion of high-coverage grassland to forestland, covering an area of 8.27 km²; the second most common change involved the conversion of forestland to high-coverage grassland, covering an area of 8.55 km². Changes in the areas of other land use categories remained relatively stable.

3.2. Landscape Pattern Analysis

3.2.1. Changes in Landscape Patterns at the Typological Level

The composite landscape fragmentation index reflects fragmentation characteristics from various perspectives (Figure 5). The AFI reflects the degree of fragmentation in terms of clustering; a higher value indicates a more clustered spatial distribution of patches and lower fragmentation. Between 2000 and 2020, the AFI for the other types of developed land significantly increased, with the fastest increase occurring between 2010 and 2015, after which it slowed. This finding indicates that other developed land areas continued to expand during this period, with increasing spatial concentration, and the patches gradually merged into contiguous areas. The AFI for rivers and canals fluctuated significantly during the study period, following a pattern of ‘rapid decline (2000–2005), sharp rise (2005–2010), stability (2010–2015), and another decline (2015–2020).’ This indicates that its spatial concentration is highly unstable, but overall, it is on a downward trend, with its spatial distribution becoming increasingly dispersed.

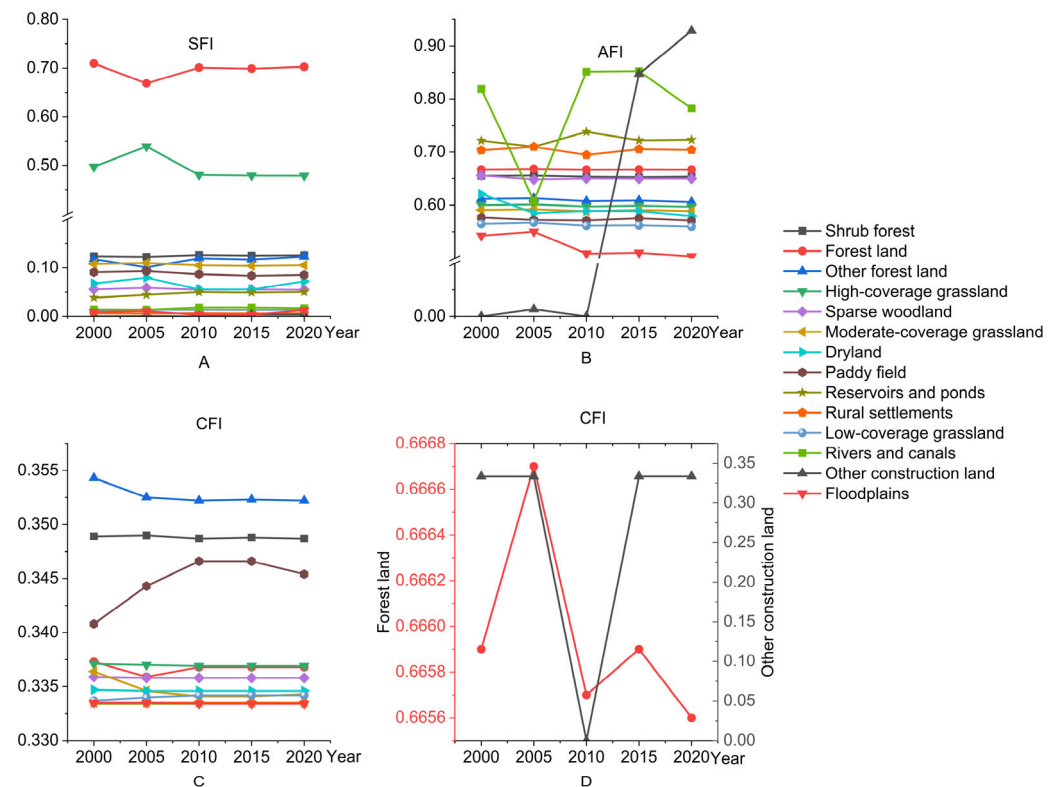


Figure 5. Changes in landscape pattern indices at the landscape pattern type level in Hainan Tropical Rainforest National Park. (A) Structure-based fragmentation index (SFI); (B) Aggregation-based fragmentation index (AFI); (C) Connectivity-based fragmentation index (CFI) for land use types excluding forest land and other construction land; (D) CFI specifically for forest land (left axis) and other construction land (right axis).

The CFI focuses on characterizing landscape fragmentation from the perspective of connectivity; a higher value indicates stronger ecological connectivity and less disruption from fragmentation. Throughout the study period, the CFI for forested land remained at the highest level (0.66–0.67) and remained dynamically stable. These findings confirm that forestland, as the landscape matrix of national parks, plays an irreplaceable and leading role in maintaining regional ecological connectivity and the functions of core habitats. The CFI of the other forestland types initially decreased but then stabilized, indicating that its connectivity underwent an initial period of degradation followed by a period of remaining at a low level. The CFI of paddy fields, on the other hand, exhibited a “rise-then-fall” pattern, which reflects the dynamic evolution of paddy fields, from initial expansion into contiguous areas (with increased connectivity) to later fragmentation (with reduced connectivity). CFI fluctuations were smaller for other land use types, and connectivity remained relatively stable overall.

The SFI focuses on characterizing the degree of fragmentation from a structural perspective. Forestland consistently maintained the highest values (0.69–0.71) throughout the study period and remained generally stable, indicating that forestland patches have complex edge shapes and a high degree of fragmentation. During the study period, the SFI of forestland decreased slightly from 2000 to 2005, increased slightly from 2005 to 2010, and subsequently stabilized, reflecting a fluctuating trend in its fragmentation characterized by a “brief easing–slight increase–stabilization” pattern. The SFI of high-coverage grassland followed an “increase–decrease–stabilization” trend, indicating that its structural fragmentation first intensified but then eased, ultimately reaching a new dynamic equilibrium. The

SFI values for the remaining land use types were relatively low and remained relatively stable throughout the study period.

3.2.2. Changes in Landscape Patterns at the Landscape Level

From 2000 to 2020, landscape fragmentation in HNTRNP exhibited significant multidimensional variations and dynamic evolution (Figure 6). The SFI indicates that after significant easing between 2000 and 2005, structural fragmentation in the study area fluctuated upward. The AFI exhibited repeated fluctuations characterized by “increased aggregation followed by a decrease”. Moreover, the CFI fluctuated downward after peaking in 2005, reflecting an overall decline in landscape connectivity. The evolutionary characteristics of these three factors indicate that fragmentation in the study area is not a single trend but rather exhibits differentiated dynamics across multiple dimensions, including structural morphology, spatial concentration, and functional connectivity. The year 2005 marked a critical turning point in the process of fragmentation, and the continued decline in landscape connectivity since then is the most significant ecological indicator to consider.

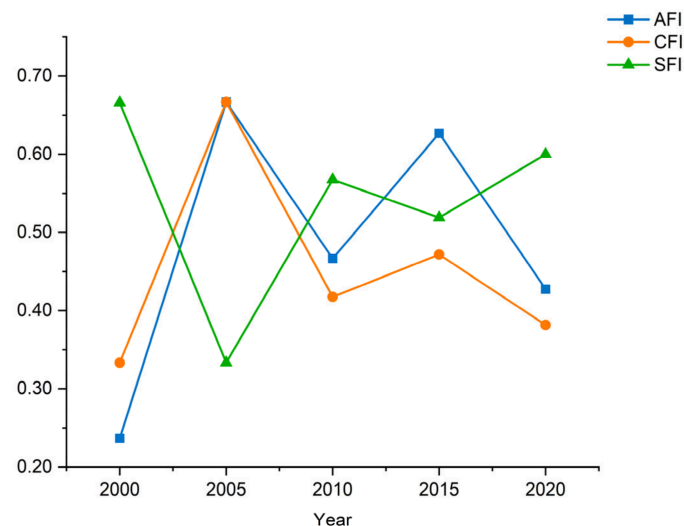


Figure 6. Changes in the landscape pattern index at the landscape level in Hainan Tropical Rainforest National Park.

3.2.3. Spatial Variation Characteristics of Landscape Indices

Using the moving window method, we created a raster map to illustrate spatial fragmentation and landscape heterogeneity and compared landscape pattern characteristics across different regions (Figure 7). During the study period, the areas where the AFI, SFI, and CFI changed were relatively similar and were primarily concentrated around roads and waterways. This finding indicates that infrastructure development—such as reservoir inundation and road construction—is a major driver of reduced landscape connectivity and spatial concentration, which in turn exacerbates landscape fragmentation in the region.

Specifically, areas where the AFI rose significantly (i.e., regions characterized by increased spatial clustering of patches and reduced fragmentation) were primarily concentrated in the southern part of Bawangling, along the Daguangba Reservoir, and near the G9811 Haishan Expressway (Shiyun section). In contrast, areas with a significant decrease in the AFI (i.e., regions characterized by reduced spatial clustering of patches and increased fragmentation) were primarily distributed around Maodao township and Nanmei village.

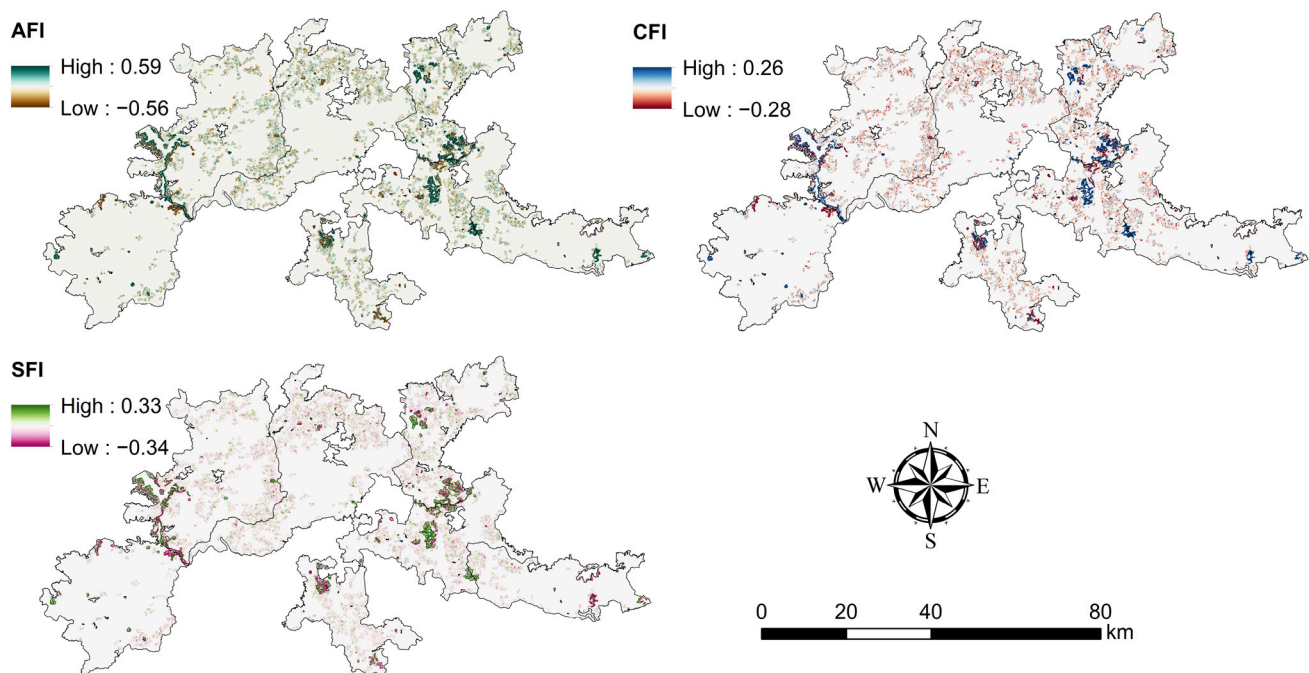


Figure 7. Spatiotemporal distribution patterns of the AFI, CFI, and SFI.

The spatial variation in the CFI further corroborates the aforementioned trend. The CFI of the Daguangba Reservoir has declined significantly, indicating that the construction of the reservoir has severely impaired landscape connectivity in the area and exacerbated fragmentation. In contrast, the CFI significantly increased in the Central Fifth Line (Yapai village–Shuiman township section), S310 (Yuanmen township section), and Maoruishi Yun village area, indicating enhanced landscape connectivity and reduced fragmentation in these regions.

Areas with a significant increase in the SFI (i.e., regions where patches were more complex in shape and fragmentation was more severe) were primarily concentrated in the Dagangba Reservoir area south of Bawangling, Yapai village in Wuzhishan, and the Liban River watershed in Limu Mountain. In contrast, areas where the SFI decreased significantly (i.e., regions where the shape of the patches became more regular and the overall degree of fragmentation decreased) were primarily concentrated in Maona village of Wuzhishan and the Shuiman township area.

3.3. Drivers of Landscape Fragmentation in the National Park

To unravel the phase-dependent dynamics dictating landscape fragmentation in HN-TRNP, we utilized the XGBoost-SHAP framework to quantify the feature contributions and relative importance of diverse drivers from 2000 to 2020 (Figure 8). SHAP dependency analysis revealed a clear dichotomy among the drivers: exacerbating factors (e.g., GDP, precipitation, human footprint) and mitigating factors (e.g., NDVI). Broadly, the paramount explanatory variables of fragmentation underwent a pronounced stage-wise trajectory, transitioning fundamentally from a regime governed by ‘natural ecological mitigation’ to one driven by ‘socio-economic exacerbation.’ Between 2000 and 2005, NDVI exerted a profound mitigating influence on fragmentation. High fragmentation hotspots were largely confined to low-to-medium NDVI zones, whereas dense vegetation cover spatially coincided with intact landscapes, underscoring the core buffering capacity of vegetation in preserving landscape integrity during this initial phase. Concurrently, precipitation acted as a secondary, positive contributor to fragmentation. From 2005 to 2010, while NDVI retained its primacy, the relative importance of its negative contribution began to wane. Conversely,

the impact of GDP surged, ascending to the second most critical driver, with high GDP exerting an increasingly potent positive effect on fragmentation. The compounding effects of precipitation and the human footprint also amplified, signaling the escalating threat of socio-economic expansion and anthropogenic disturbances to landscape contiguity. The 2010–2015 interval marked a pivotal regime shift: GDP usurped NDVI as the dominant explanatory variable for fragmentation, exerting a robust positive effect. This indicates a profound positive association between accelerating economic growth and the severe subdivision of large habitat patches. Furthermore, the exacerbating impact of precipitation intensified, and the influence of population density climbed steadily. In stark contrast, the importance of NDVI plummeted, severely decoupling its protective linkage with landscape connectivity. By 2015–2020, GDP solidified its position as the preeminent driver. The relative contributions of precipitation and the human footprint escalated further, while the mitigating capacity of NDVI continued to erode, demonstrating only marginal statistical relevance at local scales. Ultimately, socio-economic indicators and climatic factors emerged as the definitive predictors dictating the spatial configuration of the regional landscape during this terminal phase. In synthesis, the two decades from 2000 to 2020 witnessed a radical turnover in the driving mechanisms of fragmentation, shifting from an ‘NDVI-suppressed’ baseline to a ‘GDP-exacerbated’ reality. This trajectory not only spatially mirrors the encroaching overlap of anthropogenic disturbances onto intact habitats but also highlights the complex, non-linear trade-offs between mounting socio-economic pressures and the deteriorating ecological buffering capacity of natural vegetation—underscoring the severe threats to landscape integrity prior to the park’s formal establishment.

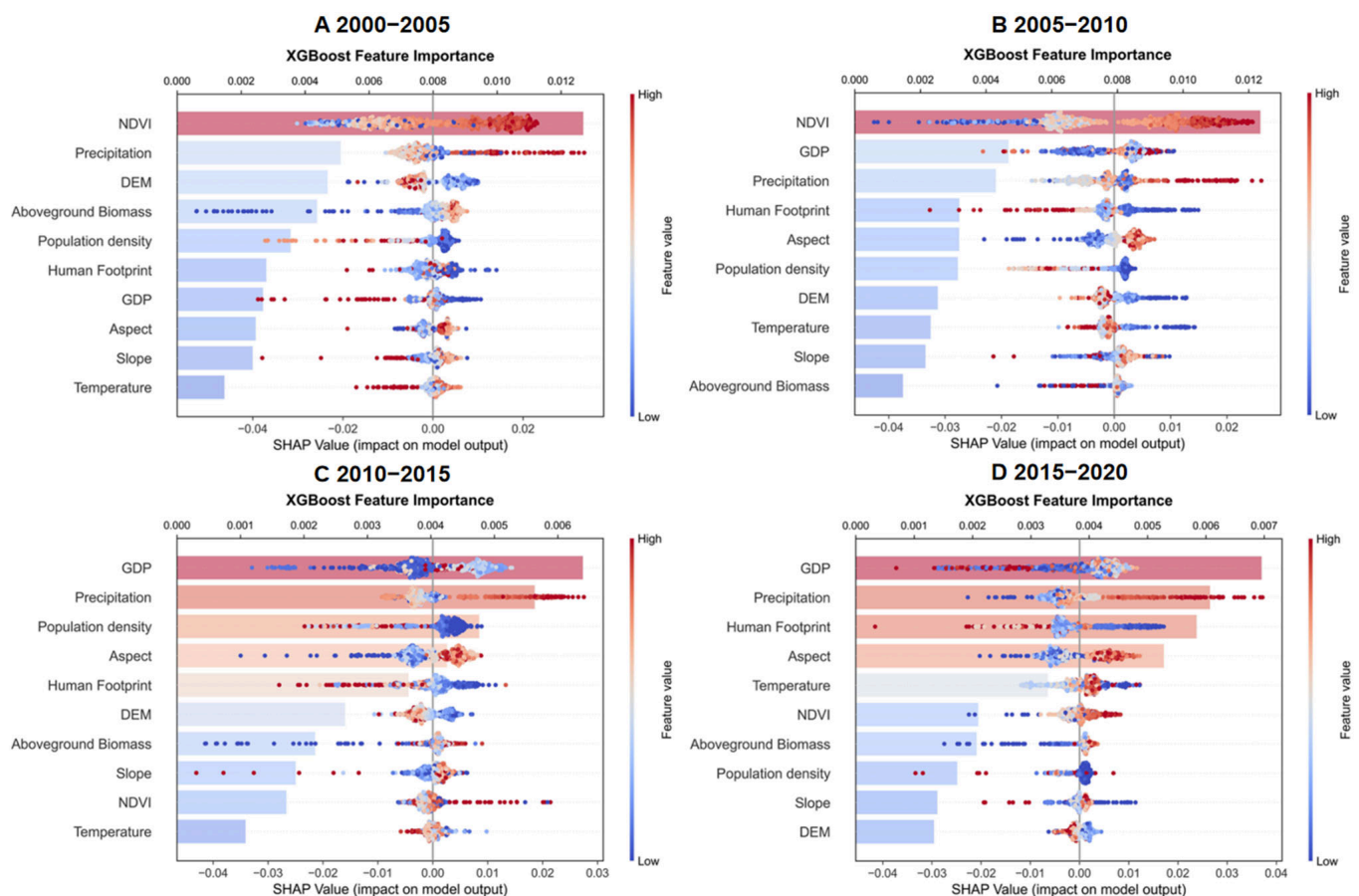


Figure 8. Relative feature importance and local SHAP effects of driving factors on landscape fragmentation: (A) 2000–2005; (B) 2005–2010; (C) 2010–2015; (D) 2015–2020.

4. Discussion

4.1. Spatiotemporal Dynamics of Landscape Fragmentation in the National Park

By employing a suite of complementary composite landscape fragmentation indices—namely, the Connectivity-based Fragmentation Index (CFI), Aggregation-based Fragmentation Index (AFI), and Structure-based Fragmentation Index (SFI)—this study systematically elucidated the spatiotemporal dynamics of landscape fragmentation in HNTRNP from 2000 to 2020. Compared with traditional single indices, composite indices can comprehensively characterize the process of fragmentation across three dimensions—ecological functional connectivity, spatial aggregation, and patch structure—thereby effectively avoiding the ecological misinterpretation that results from relying solely on traditional structural indicators.

From the perspective of overall trends, national parks exhibited significant phased changes during the study period. From 2000 to 2005, the SFI decreased significantly, whereas the AFI and CFI increased simultaneously. This finding indicates that at this stage, the structure, aggregation, and connectivity of the study area synergistically improved: as the patch shape became more regular, spatial aggregation increased, ecological connectivity improved, and fragmentation was comprehensively alleviated, which is consistent with the conclusions of Liu et al. [46]. This change resulted from policies implemented in Hainan since 2000, including the Natural Forest Conservation Project [46], the development of an “ecological province,” the planning of national-level ecological conservation areas in the central mountainous regions, and the “converting farmland to forests” initiative. The area of natural forests has increased, human disturbance has decreased, and ecological connectivity within national parks has improved, while fragmentation has decreased.

Between 2005 and 2010, a synchronized divergence occurred among the three metrics—SFI increased alongside declines in both AFI and CFI—signaling the study area’s transition into a phase of rapid landscape fragmentation. Notably, driven by the afforestation targets mandated in the 2005 Hainan Ecological Province Construction Plan, approximately 13.05% of natural forests in the central mountainous region were converted into pulpwood plantations [47]. Concurrently, subsidy policies for superior natural rubber cultivars heavily incentivized rubber planting. This policy-driven expansion caused rubber plantations to aggressively encroach upon and bisect tropical natural forests [48]. Ultimately, these anthropogenic disturbances led to a drastic surge in fragmentation, most acutely observed along the vulnerable edges of natural forests.

Since 2010, the fragmentation of national park landscapes has somewhat eased, which is consistent with the findings of Hou [48], Zhou [49], and others. Since 2010, Hainan Province has established ecological red lines in its central mountainous regions, has improved the relevant laws and regulations, and has implemented ongoing ecological conservation and restoration projects. Construction of the national park began in 2019, with efforts focused on directly restoring fragmented areas and enhancing ecological connectivity within the park.

Furthermore, the findings of this study are consistent with the conclusions of global forest fragmentation studies conducted by Zou and De Montis [36,50] and others. These findings further confirm that using structured indicators alone tends to underestimate the risk of ecological fragmentation; by combining composite indicators of aggregation and connectivity, trends in landscape fragmentation can be revealed more accurately. Connectivity and aggregation indices are crucial for assessing ecological functions; these indices are highly sensitive to human disturbances and habitat isolation, making them suitable as key indicators for evaluating habitat fragmentation.

4.2. Explanatory Power of Landscape Fragmentation Drivers

Employing the XGBoost-SHAP framework, this study systematically evaluated the primary explanatory variables dictating landscape fragmentation in HNTRNP from 2000 to 2020 (across four distinct phases). Over the study period, the dominant explanatory power underwent a fundamental shift from NDVI to GDP. Meanwhile, the influence of anthropogenic disturbances and climatic factors progressively intensified, whereas the negative mitigating capacity of natural vegetation against fragmentation markedly diminished.

Between 2000 and 2010, NDVI exhibited a significant negative correlation with landscape fragmentation. This aligns closely with the implementation of the first phase of the Natural Forest Protection Program (NFPP) and the Eco-province construction policy during the same period. The NFPP effectively halted forest logging activities, reinforced the conservation of natural forests [26], significantly reduced the intensity of human interference, and promoted rapid vegetation recovery. The pronounced negative contribution of NDVI during this period is a direct manifestation of the effectiveness of these ecological protection policies. As vegetation recovery mitigated landscape fragmentation, the impact of socio-economic factors remained relatively weak during this time.

The year 2010 served as a pivotal turning point. The regime shift in the dominant explanatory drivers governing the Hainan Tropical Rainforest National Park was intricately coupled with the concurrent development of the Hainan International Tourism Island initiative and the enforcement of natural forest conservation policies across the central mountainous region. This is closely linked to the development of Hainan International Tourism Island during the same period and the implementation of policies to protect natural forests in the central mountainous regions. The 2010 policy for the protection of mountainous areas in central China effectively curbed direct development in core protected areas and alleviated habitat fragmentation in some regions. However, rapid economic development, urban expansion, economic infrastructure construction, and increased tourism development activities [5] persistently exerted pressure on the rainforest periphery. These anthropogenic forces incessantly dissected peripheral habitats, ultimately culminating in a robust positive association between landscape fragmentation and GDP. Following the establishment of HNTRNP, China approved a series of policies designating the national park as a nondevelopment zone. These policies focus on the holistic conservation, systematic restoration, and comprehensive management of tropical rainforest resources, further promoting scientific conservation and sustainable use [26].

4.3. Recommendations for the Management of Hainan Tropical Rainforest National Park

Our findings highlight that since 2010, GDP has served as the paramount positive driver of landscape fragmentation in Hainan Tropical Rainforest National Park. To effectively alleviate sluggish forest recovery and the progressive exacerbation of habitat fragmentation, we strongly recommend the systematic implementation of vital interventions, particularly the development of ecological corridors and the promotion of green livelihood transitions. With regard to the construction of ecological corridors, the initial focus should be on areas within national parks where flagship species, including *Nomascus hainanus* and *Cervus eldii hainanus*, are primarily distributed. Enhance habitat connectivity by improving forest quality, scientifically planning ecological corridors, and strengthening the conservation and optimization of surrounding forests [51]. Second, to address the impact of transportation infrastructure, low-priority roads located within the corridor and near areas frequented by rare and endangered species should be closed and subject to strict control measures [51]. For provincial-level or higher roads that cross ecological corridors, eco-friendly corridors, such as those involving wildlife crossings, should be constructed. All corridor construction should adhere to the principle of prioritizing ecological conservation.

Give preference to green building materials that are low in toxicity and emit few chemicals. Simultaneously, monoculture plantations (e.g., rubber and areca nut) situated along the park's periphery should be incentivized to transition into mixed agroforestry systems. This strategy will facilitate the establishment of transitional ecological buffer zones, thereby effectively buffering the severe edge effects precipitated by anthropogenic activities. Most crucially, it is imperative to deepen ecological compensation mechanisms [52], to steer local communities toward green livelihood transitions, particularly through the development of under-canopy economies and ecotourism. Ultimately, these integrated approaches will reconcile regional economic expansion with biodiversity conservation, forging a resilient socio-ecological foundation for the long-term sustainable management of the national park.

Second, the areas with the most significant changes in the AFI, CFI, and SFI are distributed around waterways and roads. This is due to changes in land use in the area of HNTRNP, which currently has one large reservoir and 20 small and medium-sized reservoirs [49] and plays a crucial role in water conservation.

Therefore, scientifically coordinating the planning of reservoir locations, strictly limiting development and construction activities in reservoir areas, and reasonably planning ecological protection zones are necessary. Finally, the planting and harvesting of commercial forests are major contributors to land use change. HNTRNP currently contains 823 km² of commercial forestland, accounting for approximately 20% of the park's total area. Human activities, including repeated planting, management, and logging, have exacerbated the fragmentation of forest landscapes and increased ecological vulnerability [49]. It is recommended that economic forests in Shuiman township, Shiyun village, and the Daguangba area be phased out gradually and that ecological restoration and management of postharvest sites be strengthened.

4.4. Limitations and Future Perspectives

While the XGBoost-SHAP framework employed in this study successfully pinpointed the paramount drivers of landscape fragmentation, several limitations warrant acknowledgment. First, although the 1 km × 1 km grid resolution adequately captures macroscopic fragmentation patterns within the national park, it falls short in resolving micro-habitat fragmentation induced by human settlements. This is particularly relevant for small-scale villages pending ecological relocation (e.g., Laocun and Hongshui). Future research should integrate multi-source, high-resolution remote sensing data (e.g., sub-meter imagery) to elucidate the fine-scale impacts of anthropogenic activities on forest structure. Second, despite its efficacy in deciphering the non-linear contributions of diverse drivers, XGBoost-SHAP is inherently a statistical correlation approach that lacks mechanistic elucidations of underlying ecological processes. Subsequent studies should incorporate process-based ecological models to validate the mechanistic pathways through which socio-economic factors precipitate forest fragmentation. Lastly, our temporal analysis across five nodes between 2000 and 2020, while proficient at capturing long-term trajectories, may inadvertently mask abrupt, pulse-like disturbances. Furthermore, owing to data latency following the park's official designation, our current scope precludes post-2020 developments. Future investigations will capitalize on updated datasets to facilitate near-real-time monitoring of fragmentation dynamics following the park's establishment.

5. Conclusions

By coupling composite landscape fragmentation indices (CFI/AFI/SFI) with the XGBoost-SHAP framework, this study systematically elucidated the spatiotemporal dynamics and driving mechanisms of landscape fragmentation in Hainan Tropical Rainforest National Park. Our findings revealed pronounced phase-dependent characteristics in

fragmentation, with 2005 acting as a pivotal turning point. Between 2000 and 2005, fragmentation was significantly mitigated, primarily driven by vegetation recovery under the Natural Forest Protection Program. However, from 2005 onwards, the positive feature importance of GDP surged due to accelerating urbanization and infrastructure development. By 2010, GDP had emerged as the dominant explanatory variable, driving a resurgence in landscape fragmentation. Furthermore, the 823 km² of commercial forest plantations currently residing within the park exacerbate fragmentation; therefore, future policies should orchestrate their orderly phase-out and near-natural restoration. Ultimately, this study offers a robust scientific basis and empirical evidence for the sustainable management and targeted ecological restoration of the national park.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su18147486/s1>, Table S1: Semi-variogram fitting parameters ($C_0/(C_0 + C)$ and R^2) for landscape fragmentation indices across varying moving window radii. References [53,54] are cited in the Supplementary Materials.

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

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