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Article

Study into the Evolution of Spatio-Temporal Characteristics and Driving Mechanisms of Production–Living–Ecological Spaces on the Indochina Peninsula

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Abstract: Influenced by historical background, regional economic development, and the frequent occurrence of armed conflict, the human–earth relationship in the Central and Southern Peninsula, which is located in a "fragmented zone", is characteristic of the region. The Indochina Peninsula has now become an area of interest for the study of spatial changes in production–living–ecological spaces (PLES). Taking the Indochina Peninsula as the study area, this paper explores the evolution of the spatio-temporal patterns of PLES and its driving mechanism in the Central and Southern Peninsula, from 2010 to 2020, based on the grid scale. Methods such as the land-use transition matrix, land-use dynamics index, and Geographically and Temporally Weighted Regression (GTWR) were used in our model. Our results show that, from 2010 to 2020, ecological space dominated the PLES pattern on the Indochina Peninsula but its area gradually decreased, accompanied by a sharp increase in the areas of productive and living spaces. The area of PLES interconversion on the Indochina Peninsula in 2010–2020 was 212818.70 km2, and it is characterized by the conversion of ecological space into productive space, as well as the interconversion of woodland ecological and grassland ecological spaces. In addition, the intertransfer of production and ecological spaces was distributed in a network-like manner throughout the Indochina Peninsula, while the transfer of living space was distributed in a point-like manner. The migration path of the center of gravity of PLES on the Indochina Peninsula demonstrates a significant directional difference. The PLES's pattern evolution was affected by the degree of multiple factors, with a significant spatial and temporal heterogeneity. The positive and negative feedback effects of the factors were distributed in different areas and in different transfer directions.

Keywords: the Indochina Peninsula; the production-living-ecological spaces; GTWR

1. Introduction

Since the 1990s, there have been several mechanisms for geopolitical and economic co-operation across the Indochina Peninsula; such co-operation exists between countries as a top-level strategy and influences land-use changes on the Indochina Peninsula in different forms and dimensions, and to different degrees [1]. As the trend in regional political and economic integration intensifies and international attention to the Indochina Peninsula continues to grow, transregional economic cooperation and projects such as "alternative planting" and the construction of border roads have had a profound impact on land use and land cover in the area [2-4]. Due to its special location and
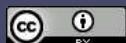
economic development mode, the Indochina Peninsula is now an active zone of land-use change [2]. Strengthening the study of land-use change across the Indochina Peninsula is of great significance for the improvement of its sustainable development, and for the ecological and environmental benefits of the region.

The most important feature of regional land-use change is the mutual transformation between land-use types and their dominant functions, i.e., the mutual transfer between three land-use function types, namely, production space, living space, and ecological space [5-7]. PLES is a comprehensive territorial spatial division, which is based on the multifunctional perspective of land use [8,9]. Production space refers to the land used for human survival and livelihood, and is an important aspect of the development of PLES; living space refers to the land used for human social habitation, which is the core of PLES; and ecological space refers to the natural environment on which human beings depend for their survival, and which is the prerequisite and direction of the development of PLES [10,11]. As a result of the evolution of the territorial system of human–land relations [12], exploring PLES driving mechanisms can effectively explain the relationship between human activities and the evolution of PLES patterns [13]. Currently, the driving mechanism behind PLES pattern evolution is studied using multiple linear regression [14] and principal component analysis [15], but these methods only focus on the mathematical logic among factors: they cannot explain the geographic logic of the factors or the real spatial characteristics of the regression parameters; nor can they respond to the spatial heterogeneity between the dependent variables and their influencing factors in geographic phenomena [16]. Some scholars extended ordinary linear regression by using Geodetector [17,18], Geographically Weighted Regression (GWR) [19,20], and Multiscale Geographic Weighted Regression (MGWR) [21]; these explain the local spatial relationships and spatial heterogeneity of variables well [22]. However, the influencing factors involved in PLES pattern evolution are both spatially and temporally non-stationary; because of this, the traditional regression and constant coefficient spatial econometric models cannot satisfy the research need to identify the direction and strength of the drivers of PLES pattern evolution under different spatial and temporal distributions. The Geographically and Temporally Weighted Regression (GTWR) model proposed by Huang et al. [23] can effectively deal with the problem of spatio-temporal heterogeneity and has been widely used in the study of spatio-temporal heterogeneity of socio-economic and environmental pollution drivers [24,25]. In this paper, based on the grid scale, the GTWR model is applied to the evolution of the PLES pattern and the analysis of the driving factors throughout the Indochina Peninsula, taking into account the spatial and temporal non-stationarity of the factors. It proposes a new research idea, which will provide the basic data and reference for sustainable development planning across the Indochina Peninsula, and also the basis for subsequent research on land-use change throughout the Indochina Peninsula. In addition, it provides a reference for subsequent research on the driving mechanisms, ecological assessment, and simulation prediction of land-use change in the area.

2. Materials and Methods

2.1. Site description

Due to factors such as historical background, regional economic cooperation, and frequent armed conflicts, human–land relations across the Indochina Peninsula are typified by regional characteristics. The overall region is known as a fragmented zone in the world [26,27]. In this paper, Myanmar, Vietnam, Laos, Thailand, and Cambodia, all located on the Indochina Peninsula, were selected as the study area (Figure 1). As a relatively independent geographic unit, the Indochina Peninsula has an important geopolitical and economic strategic value, and is an important arena for competition and power games among extra-regional powers [28,29]. The implementation of many international economic cooperation and resource development projects, especially the "Golden Four Corners" program and "Alternative Cultivation" policy shared by China, Myanmar, Thailand, and the Lao People's Democratic Republic, brought about significant change in the land use/cover status of the region [30,31]. Together, the special characteristics of land-use patterns [32-34], tropical rain

forests in Southeast Asia, and widely distributed alternative plantation crop areas [35] make the Indochina Peninsula an area of great interest to many international organizations studying LUCC and the ecological environment.
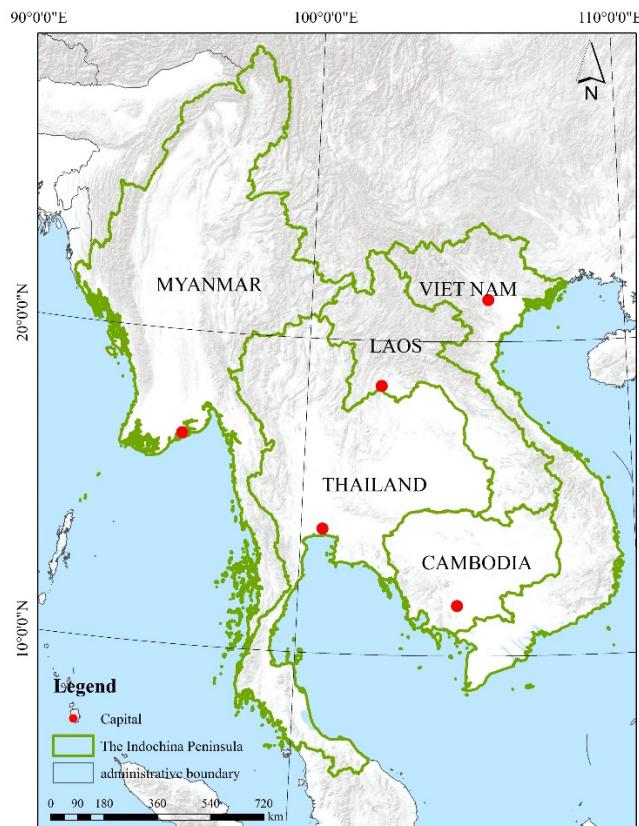

Figure 1. Schematic of the study area.

2.2. Data source

Data were gathered from the GlobeLand30 land cover/land use dataset (http://www.globallandcover.com/) and the SEDAC population density dataset (https://sedac.ciesin.columbia.edu/) for 2010 and 2020. The data were pre-processed and reclassified to obtain the 2010 and 2020 PLES data for the Indochina Peninsula (Table 1).

Table 1. Classification system of PLES.

Primary category	Secondary category	Data source
The production space	1—Agricultural production space;	GlobeLand30: cropland
	2—Industrial production space;	GlobeLand30: artificial surface (excluding the range of living space defined by SEDAC)
The living space	3—Urban living space;	SEDAC: the population density is greater than 1500/km2
	4—Rural living space;	SEDAC: the population density is 300–1500 /km2
The ecological space	5—Forest ecological space;	GlobeLand30: forest, bush
	6—Grassland ecological space;	GlobeLand30: grass

| | 7—Water ecological space; | GlobeLand30: wetlands, water, glaciers and permanent snow cover |
| | 8—Other ecological spaces | GlobeLand30: tundra, bare land |

In this paper, road networks, water systems, population densities, night lighting, precipitation, Normalized Difference Vegetation Index (NDVI), and armed conflict events were selected as the influencing factors for the evolution of the PLES patterns in the Indochina Peninsula region from four aspects: human location, socio-economics, natural environment, and geopolitics. Road networks affect land use in a unique way. On the one hand, road construction promotes the development of construction land; on the other hand, it takes up a large amount of forest and grassland, resulting in the reduction of forest and grassland areas. At the same time, slope greening and ecological protection undertaken in the process of road construction were shown to increase the area of shrubs and bushes [36]. In addition, proximity to a river system affects the distribution of productive space: the closer the river, the more productive the space [37]. Population density is another factor directly influencing the spatial distribution of land use/cover in the study area, with more densely populated areas having higher levels of living-space development. Furthermore, the Nighttime Lighting Index reflects the level of regional economic development and compensates for the lack of GDP data. Precipitation impacts ecological space spatial distribution, while NDVI directly reflects the changes in forest land, grassland, cultivated land, and other land types. Finally, geopolitics is also an easily overlooked influence for the Indochina Peninsula, where the location and frequency of armed conflict events have a dramatic effect on land-type change [38]. The data sources for each influencing factor are shown in Table 2.

Table 2. Driving factors and data sources.

Datatypes	parameter	factor	Introduction to data	Data source
Humanistic location	X1	Distance to railway	Indicates the distance from the centre of each pixel to the nearest railway line	https://www.openstreetmap.org https://www.naturalearthdata.com/
	X2	Distance to road	Indicates the distance from the centre of each pixel to the nearest road	Socioeconomic Data and Applications Center | SEDAC (columbia.edu) https://www.openstreetmap.org
	X3	Distance to river	Indicates the distance from the centre of each pixel to the nearest river	https://www.openstreetmap.org
social economy	X4	Night Lights	Indicates the nighttime light value within each pixel	VIIRS Nighttime Light (mines.edu) geodata.cn
	X5	population density	denotes the value of population density within each pixel	https://sedac.ciesin.columbia.edu/
natural environment	X6	precipitation	Indicates the value of rainfall within each pixel	Climatic Research Unit - Groups and Centres (uea.ac.uk)
	X7	Normalized Difference	Indicates the NDVI value within each pixel	https://ladsweb.modaps.eosdis.nasa.gov/

		Vegetation Index(NDVI)		
geopolitics	X8	Armed conflict events	Indicates the number of deaths from armed conflict in each pixel.	ACLED	Bringing Clarity to Crisis (acleddata.com)

2.3. Data preprocessing

OSM data require geometric repairing, cropping, merging, fusing, etc., and Euclidean distances must be calculated. Armed conflict events require data cleansing and interpolation. Compared to other interpolation methods, IDW is a precision interpolation and ensures that the predicted value at the sampling point is completely consistent with its real value. In this study, IDW was used to spatialize fatalities in armed conflicts. All factor data were standardized, with a uniform scale, and projected to the "Krasovsky_1940_Albers" coordinate system with a resolution of 250 m. The resolution of the PLES data was 30 m, which facilitated subsequent processing.

To verify whether initially selected influencing factors can be used for modeling the regression model, a covariance line analysis of the influence factors is required [39,40]. In this paper, the variance inflation factor (VIF), eigenvalue, etc., were selected to determine whether there was covariance among the influencing factors. When the VIF is greater than 10, it indicates that there is covariance among various factors; this must be eliminated to render the next modeling more feasible [41]. As shown in Table 3, the VIF values of the influencing factors are less than 10, so there is no multicollinearity; accordingly, they can be used for modeling the regression model.

Table 3. collinearity diagnostics.

VIF	X1	X2	X3	X4	X5	X6	X7	X8
2010	1.125	1.068	1.069	1.283	1.326	1.061	1.104	1.035
2020	1.14	1.121	1.068	1.065	1.088	1.072	1.077	1.04
2010-2020	1.131	1.077	1.063	1.166	1.196	1.06	1.085	1.038

After pre-processing the driver data, a 15 km × 15 km fishing network was generated based on the ArcGIS platform; 8,539 sampling points were yielded in the five-country region of the Indochina Peninsula. Factors were resampled uniformly up to 15 km, and factor attribute values were extracted based on the sampling points. The area and percentage of the PLES within the unit grid were counted to obtain information on the evolution of the PLES (dependent variable) and the data on the driving factors (independent variables). The driving mechanisms behind PLES pattern evolution in the five countries of the Indochina Peninsula were analyzed using the GTWR model.

2.4. Research Methods

2.4.1. Transfer matrix of PLES

The land-use transition matrix was used to analyze the evolution of PLES patterns. The essence of the transfer matrix is to use the transfer probability of a Markov chain and the steady state equation to analyze the dynamic characteristics and development trends of land-use change [42], with the following expression:

$$S_{ij} = \begin{bmatrix} S_{11} & \dots & S_{1n} \\ & \dots & \\ S_{n1} & \dots & S_{nn} \end{bmatrix} \qquad (1)$$

Where S_{ij} is the number of transfers from spatial type i to spatial type j in the study area and S_{nn} is the PLES type area.

2.4.2. Land-use dynamics index

Land-use dynamics refers to the quantitative change in land-use types in a certain period of time, mainly reflecting the intensity of land-use change and regional differences in the rate of change, and characterizing the impact of human activities on regional land use, so as to better guide regional land use [43]. It is mainly divided into single land-use dynamics and comprehensive land-use dynamics : single land-use dynamics is used to describe the change in a certain land-use type in the region within a certain time frame, while comprehensive land-use dynamics describes the overall rate of land-use change in the entire region [44].

$$K = \frac{U_a - U_b}{U_a} \times \frac{1}{T} \times 100\% \tag{2}$$

Where K is the single dynamic index of a land-use type in the study period, U_a is the area of a land-use type at the beginning of the study, U_b is the area of the land-use type at the end of the study, and T is the time interval.

$$L_c = \left[\frac{\sum_{i=1}^{n} \Delta L_{U_{i-j}}}{2 \sum_{l=1}^{N} L_{U_i}}\right] \times \frac{1}{T} \times 100\% \tag{3}$$

Where, L_c is the comprehensive land-use dynamics index in the study area, L_{U_i} is the area of land-use type in the previous period, $\Delta L_{U_{i-j}}$ is the absolute value of the area of land of category i converted to land-use type j in the study time period, and T is the time interval.

2.4.3. Standard deviation ellipse model

Using the center of gravity, the long and short axes, and the azimuthal angle of the standard deviation ellipse, can portray the overall distribution characteristics, the degree of agglomeration, and the center of agglomeration of each type of territorial spatial area. The smaller the area of the ellipse and the standard distance between the x and y axes, the higher the degree of agglomeration, and vice versa [45]. In this study, analysis of the standard deviation ellipse of production space, living space, and ecological space was conducted to explore the distribution range and directional trend of each space, and further analyze the evolution characteristics.

$$X = \frac{1}{N}\sum_{i=1}^{n} x_i \tag{4}$$

$$Y = \frac{1}{N}\sum_{i=1}^{n} y_i \tag{5}$$

$$\tan \theta = \frac{(\sum_{i=1}^{n}\hat{x}_i^2 - \sum_{i=1}^{n}\hat{y}_i^2) + \sqrt{(\sum_{i=1}^{n}\hat{x}_i^2 - \sum_{i=1}^{n}\hat{y}_i^2)^2 + 4(\sum_{i=1}^{n}\hat{x}_i^2\hat{y}_i)^2}}{2\sum_{i=1}^{n}\hat{x}_i\hat{y}_i} \tag{6}$$

Where X and Y denote the coordinates of the center of gravity position of the spatial unit of the land-use type, x_i and y_i denote the value of the coordinates of the spatial unit, θ denotes the angle of the ellipse, $\hat{x}_i$ and $\hat{y}_i$ denote the deviation from the center coordinates to the center of gravity coordinates of each spatial unit, respectively. The main parameters of a standard deviation ellipse are the position of the center point, the long axis, the short axis, and the angle of rotation.

2.4.4. GTWR model

GTWR is a regression analysis method that incorporates temporal and spatial information on the basis of Ordinary Linear Regression (OLR) to study spatio-temporal heterogeneity; it is capable of reflecting the change patterns in the spatio-temporal non-stationarity of the regression coefficients [23]. The formula is:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k (u_i, v_i, t_i) X_{ik} + \varepsilon_i \tag{7}$$

where (u_i, v_i) denotes the latitude and longitude coordinates of the ith sample point, t_i denotes the time of observation, y_i denotes the value of the dependent variable for the ith sample point, and X_{ik} denotes the kth explanatory variable for the ith sample point. ε_i is the model error term, $\beta_0(u_i,v_i,t_i)$ denotes the regression constant for the ith sample point, and $\beta_k(u_i, v_i, t_i)$ denotes the regression coefficient of the kth explanatory variable for the ith sample point. This is expressed as follows:

$$\hat{\beta}(u_i, v_i, t_i) = [X^T W(u_i, v_i, t_i)X]^{-1} X^T W(u_i, v_i, t_i)Y \tag{8}$$

Where $W(u_i, v_i, t_i)$ denotes the weight of spatio-temporal location i. The GTWR model determines the weight of the influence of the values of other sample points on the regression sample points by constructing a spatio-temporal weight matrix.

The process of constructing a weight matrix based on spatio-temporal distance is shown below. First, the spatial distance between the sample points is calculated by applying the Euclidean distance formula.

Since the different units of measurement for temporal and spatial distances are prone to affect the results, the temporal and spatial distances are calculated as follows:

$$(d^{ST})^2 = \lambda(d^S)^2 + \mu(d^T)^2 \tag{9}$$

The weight function is usually chosen as either a Gaussian or a bi-square function; these can be transformed into a weight function after substitution, and the weight matrix is calculated as follows:

$$W_{ij} = exp\left\{-\frac{[(u_i - u_j)^2 + (v_i - v_j)^2] + \tau(t_i - t_j)^2}{(h_s)^2}\right\} \tag{10}$$

Where $\tau = \mu/\lambda, \mu, \lambda$ are the weights used to balance the different effects, d_{ij}^{ST} is the spatio-temporal distance between the sample points, and h is a non-negative parameter called the spatio-temporal bandwidth.

3. Results

3.1. Analysis of the dynamics of spatio-temporal patterns in PLES

Ecological space dominates the PLES of the Indochina Peninsula. In the 10-year period from 2010 to 2020, the areas of production and living spaces increased dramatically, while the area of ecological space decreased correspondingly; the trend in change is consistent with the characteristics of the regional resources and economic development (Figure 2). From the point of view of changes in the area of each type of space, with population growth and economic development, both urban and rural living spaces expanded, with additional areas of 3,460 and 2,029 km2 in the 10-year period, respectively. The Indochina Peninsula is relatively backward in terms of economy and industry, but has developed its agriculture. Traditional means of farming such as slash-and-burn and straw burning have, therefore, been reduced. In contrast, the expansion of economic forests, commercial logging, and the expansion of rubber forests, such as artificial plantations and rubber forests have increased. These activities, together with regional economic cooperation, have contributed to the rapid expansion of agricultural and industrial production space, while the ecological spaces of woodland and grassland have decreased at different levels, with woodland decreasing by 26,549 km2 and grassland decreasing by 3,624 km2, making woodland ecological space the land-use type with the greatest change in area on the Indochina Peninsula.

There are spatial differences in the rate of change of PLES in the Indochina Peninsula region (Table 4). From 2010 to 2020, the integrated land-use dynamics of the Indochina Peninsula was 0.16%, and those of Myanmar, Vietnam, Laos, Cambodia, and Thailand were 0.07%, 0.3%, 0.14%, 0.71%, and 0.13%, respectively. Cambodia had the fastest rate of change in the spatial pattern of PLES, Laos the next fastest, and Myanmar the slowest. The rate of spatial pattern change was influenced by regional economic development. The Indochina Peninsula experienced a rapid expansion in industrial production space with a motivation of 9.84%, followed by urban living space with a motivation of

3.44%. Rural living space was relatively stable in area, having a low growth rate with a motivation of 0.18%. Forest land, grassland, and other ecological spaces had a motivation of -0.24%, -0.36%, and -0.42%, respectively, with other ecological spaces decreasing at the fastest rate.

From 2010 to 2020, the industrial production space of the Lao PDR was expected to   change at the highest rate of 63.19%, following the Lao Government's active promotion of the strategy for "resources for capital". Thailand's other ecological spaces were expected to undergo drastic changes, with a 422.08% change in dynamics; this was mainly influenced by Thailand's national development strategy driven by commercial logging, urban development, and the acquisition of international benefits [46].
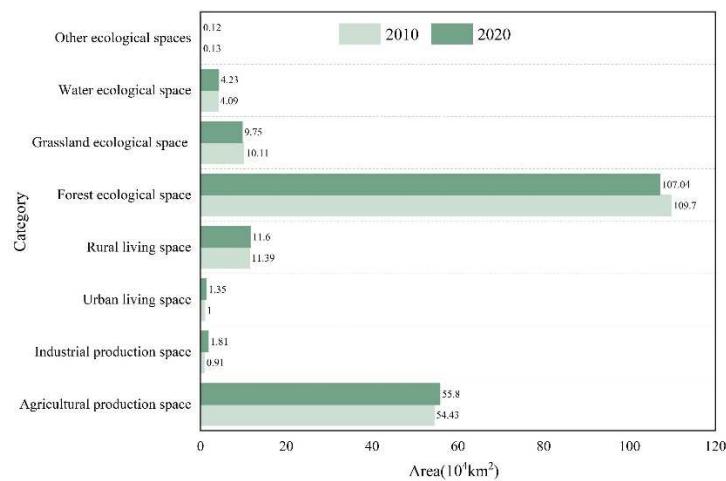

Figure 2. Land-use dynamics index for PLES on the Indochina Peninsula.

Table 4. Land-use dynamics index for PLES in the five countries on the Indochina Peninsula.

id	category	Laos	Cambodia	Myanmar	Thailand	Viet Nam	the Indochina Peninsula
1	Agricultural production space	0.80%	1.97%	-0.14%	0.01%	0.47%	0.25%
2	Industrial production space	63.19%	7.56%	5.50%	13.69%	10.85%	9.84%
3	Urban living space	2.53%	6.63%	-0.42%	7.45%	2.12%	3.44%
4	Rural living space	3.14%	1.12%	1.64%	-1.59%	0.42%	0.18%
5	Forest ecological space	-0.18%	-1.23%	-0.05%	0.00%	-0.55%	-0.24%
6	Grassland ecological space	0.10%	-0.70%	-0.02%	-1.05%	-0.58%	-0.36%
7	Water ecological space	1.96%	0.42%	0.37%	-0.51%	1.57%	0.34%
8	Other ecological spaces	1.40%		-2.62%	422.08%	8.21%	-0.42%

comprehensive land-use dynamic index	0.14%	0.71%	0.07%	0.13%	0.30%	0.16%

3.2. Analysis of the evolutionary process of PLES spatio-temporal

3.2.1. Quantitative analysis of land-use type shifts in PLES

From 2010 to 2020, the Indochina Peninsula had an area of 212,818.70 km2 of interconversion of PLES utilization, manifested in the conversion of ecological space into production space, and the interconversion of woodland and grassland ecological spaces (Figure 3). The transfer in of industrial production space came predominantly from agricultural production space, accounting for 49.48% of the industrial production land by 2020. Transfer out was mainly converted to agricultural production space, accounting for 76.11% of the total transfer out of industrial production. The change in woodland ecological space was predominantly attributed to grassland ecological and agricultural production spaces; by 2020, the transfer in accounted for 3.62% and 1.87% of the area of woodland ecological space, respectively. The area of forest ecological space converted to grassland ecological and agricultural production spaces was 39,470 km2 and 41,370 Km2, respectively, accounting for 43.69% and 45.79% of the total transfer out of forest land. The water ecological space was predominantly converted to agricultural production space, accounting for 54.21% of the transfer out of water ecological space.

Agricultural production space and woodland ecological space are the main land types in the five countries of the Indochina Peninsula and, from 2010 to 2020, there were shifts in the various types of PLES. In Myanmar and Laos, the most drastic land transfer of three biospatial land types was the interconversion of woodland and grassland ecological spaces, followed by the interconversion of woodland ecological and agricultural production spaces. Thailand's land transfer of PLES mainly focused on the interconversion of woodland ecological and agricultural production spaces, being 8,334.99 km2 and 7,700.08 km2, respectively. The interconversion of three biospatial land types in Cambodia and Vietnam focused on the transfer of woodland ecological to agricultural production spaces. The quantitative transfer mainly focused on the conversion of woodland ecological space into agricultural production and grassland ecological spaces, with the areas of woodland converted to agriculture being 11,810.08 km2 and 9,744.81 km2, respectively. The areas of land converted to grassland were 2,551 km2 and 7,455.21 km2, respectively. The reason for this may be that changes in various types of land areas from expansion to contraction, or from contraction to expansion, corresponded to the transformation in the stage of regional economic development [47]. With the construction of the regional economic corridor, the five countries of the Indochina Peninsula have changed from traditional agricultural methods to commercial agricultural production, and the center of gravity has tilted from the primary industry to the secondary and tertiary industries: this had a direct impact on the transformation of ecological and production spaces.
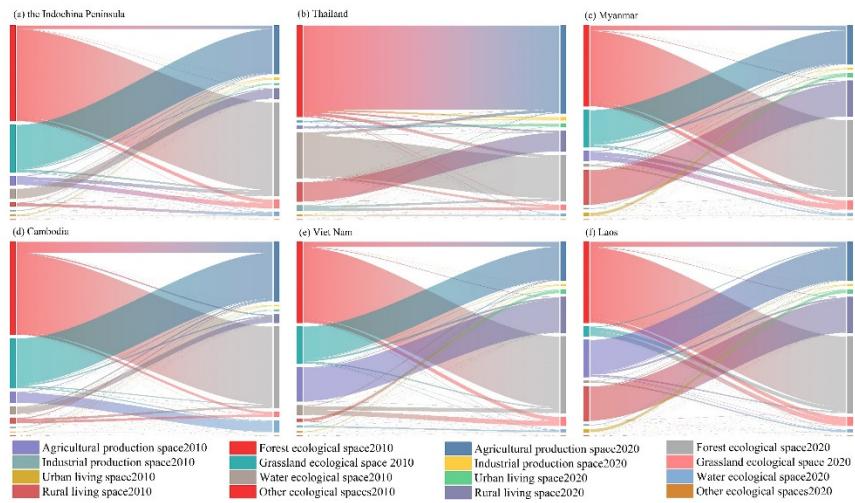
Figure 3. Amount of land-use type transfers in PLES from 2010 to 2020. (a) the Indochina Peninsula, (b)Thailand, (c)Myanmar, (d)Cambodia, (e)Viet Nam, (f)Laos.

3.2.2. Analysis of the process of transferring land-use types in PLES

The conversion of production and ecological spaces is distributed as a network throughout the Indochina Peninsula, and the conversion of living space is distributed as points (Figure 4). The conversion of forest and grassland ecological spaces is distributed in the western region of Myanmar, the northeastern and southern regions of Thailand, and the entire territories of Vietnam and Cambodia. From 2010 to 2020, the conversion of forest ecological space into agricultural production space was uniformly distributed across the Indochina Peninsula. The conversion of agricultural production space into rural living space was distributed in a point-like manner in the southern region of Yangon and the central region of the Sagaing region in central Myanmar, Chonburi Province in Thailand, Batuyi, Battambang, and Kandan provinces in Cambodia, Binh Duong, Đồng Nai, Bạc Liêu, and Sóc Trăng provinces in Vietnam, and the western region of Laos. The conversion of agricultural production space into industrial production space was distributed in Myanmar, Vietnam, central Thailand, and central Cambodia, but with almost none in Laos. The conversion of grassland ecological space into agricultural production space was concentrated throughout the eastern and central regions of the Indochina Peninsula, with very little distribution in the southwestern region. The conversion of rural living space into agricultural production space was concentrated in the central region of Thailand and the southeastern region of Cambodia. The conversion of the water ecological space and agricultural production space into each other was evenly distributed across the Indochina Peninsula. The exception to this was Laos, where the main food crop is rice: some cultivated land and forested land were converted into agricultural production space in order to improve agricultural production conditions. Rice is the main food crop across the Indochina Peninsula, and in order to improve agricultural production conditions, some areas of cultivated and forest land have been converted into paddies. The conversion of industrial production space into agricultural production space is discretely distributed across the Indochina Peninsula from northwest to southeast in the middle of Myanmar, Cambodia, and Thailand.
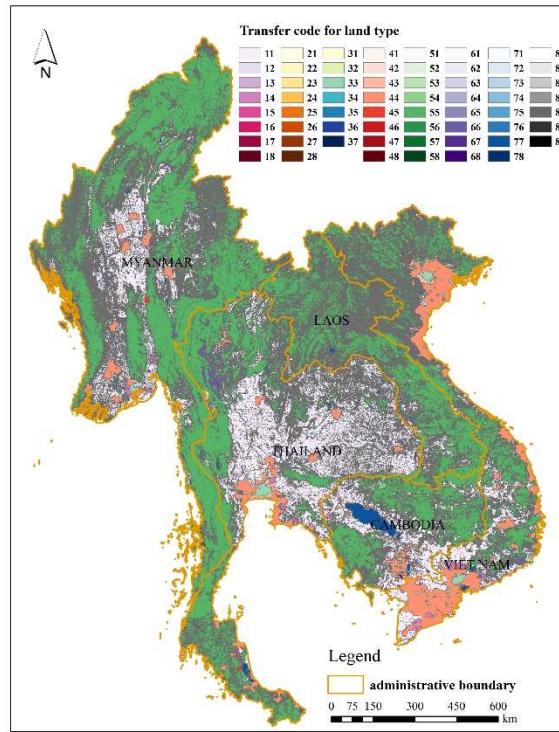
Figure 4. Patterns of PLES on the Indochina Peninsula from 2010 to 2020.

The migration path of the center of gravity of PLES on the Indochina Peninsula demonstrates significant directional differences (Figure 5). Overall, from 2010 to 2020, the production space migrated to the southwest, the living space to the northeast, and the ecological space to the east. Compared with the living space, the production and ecological spaces experienced a more directional tendency, were more influenced by Myanmar, Thailand, and Cambodia, and also demonstrate a more significant trend in discrete distribution. During the same period, PLES migrated to the southwest, the center of gravity of production space moved insignificantly, the standard deviation ellipse area did not change much, the X-axis decreased, and the Y-axis increased, indicating that the production space distribution across the Indochina Peninsula was more balanced, and mainly in the northwest–southeast direction. The living space shifted to the northeast direction, and the standard deviation ellipse area for living space decreased in both the X- and Y-axes, indicating that the living space had a tendency to shrink in all directions; this shows a tendency to shift from a discrete to an agglomerated distribution, this phenomenon being mainly concentrated in the regions of Thailand, Laos, and Vietnam. The direction and extent of the standard deviation ellipse distribution of the ecological space is similar to that of the production space, indicating that the trend in the living space is stronger in the northwest–southeast direction than in the northeast–southwest direction. The center of gravity of the ecological space shifted to the east, indicating that the distribution of the ecological space was susceptible to the influence of Laos and Vietnam in the eastern region of the Indochina Peninsula.
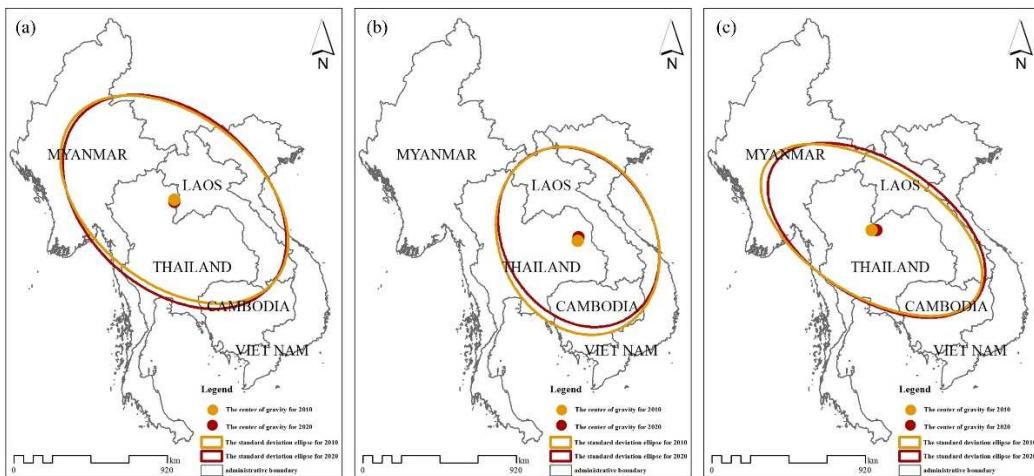
Figure 5. The standard deviation ellipse of PLES on the Indochina Peninsula from 2010 to 2020. (a) the production space, (b) the living space, (c) the ecological space.

3.3. Analysis of PLES spatio-temporal pattern evolution drivers

In this study, road networks, water systems, population densities, night lighting, precipitation, NDVI, and armed conflict events were selected as the influencing factors in the evolution of PLES spatio-temporal patterns in the Indochina Peninsula region from the four aspects of humanistic location, socio-economics, natural environment, and geopolitics. Covariance diagnostics and standardization were performed on the influencing factors, and the results demonstrate that all the factors satisfy the model construction criteria. The GTWR model was applied to regression analysis of the sample data to obtain the regression coefficients of each influencing factor on the evolution of the PLES pattern, based on the grid scale from 2010 to 2020. The model was used to analyze the degree of influence of each factor on the evolution of the PLES pattern at different spatial and temporal locations under the double effect of time and space. The GTWR model was applied to simulate the eight spatial types: different R^2 and bandwidths were obtained, with an optimal model fit of 0.56 and a mean value of 0.4, the lowest fit being that of the watershed ecological space. The magnitude of the regression coefficients represents the degree of influence of each influencing factor on the evolution of the three spatial patterns (Table 6). The transfer of land-use types in the PLES of the Indochina Peninsula was influenced by social context and regional environment. Population density (X5) was the factor that most influenced the changes in pattern of the three living spaces; regions with a high population density were prone to expansion of production and production space, and ecological space was prone to being squeezed. In 2020, the factors influencing the agricultural production space and the ecological space of the forest land had opposing roles. Increased population density promoted the development of agricultural production space, while inhibiting the development of woodland ecological space. The armed conflict factor (X8) had a positive feedback effect on urban living space and inhibited the conversion of other spatial types into the promotion of agricultural production space, woodland, and other ecological space. This is because the political and ethnic conflicts in Myanmar, as well as turbulence in Thailand's political environment, and the potential for social instability, etc., intensified the outbreak of armed conflict events to a certain extent, affecting the environment of human life and production. Furthermore, in 2020, possibly because of the move to promote agricultural production space, it appears that agriculture was not affected by the waves of armed conflict. Instead, agriculture production space played a facilitating role to a certain extent. The distance to the road network (X1, X2) factor was positively related to the ecological space of the woodland, which may be due to the increase in green environments such as street trees, shrubs, and grasses on both verges on the sides of the road. Border road construction improves accessibility, but road planning and construction also encroach on productive living space to some extent. The distance from the water system factor (X3) and precipitation (X6) were positively proportional to the ecological space of forest land, and inversely proportional to other spatial types. The Indochina Peninsula is rich

in precipitation, has a dense water network, is rich in forest resources, and tropical rainforest occupies a wide range of areas; however, this inhibits the expansion of production space. Night lighting (X4) was proportional to the relationship between industrial production space and human life space, reflecting the regional economic level: the higher the level of economic development, the more frequent the human activities, and the closer to the urban built-up area. NDVI (X7) reflects the vegetation cover, which was positively proportional to the ecological space of the forest land and grassland; an increase in the vegetation cover indicates the expansion of the ecological space of the forest land and grassland.

Table 6. GTWR model estimation result.

| year	category	X1	X2	X3	X4	X5	X6	X7	X8
	Agricultural production space	-0.264	-0.169	0.011	-3.810	4.692	-0.250	-0.478	-0.286
	Industrial production space	-0.021	-0.034	-0.010	0.038	0.617	-0.002	-0.018	-0.063
	Urban living space	-0.127	-0.119	-0.092	-1.857	6.327	-0.079	-0.038	1.049
2010	Rural living space	-0.001	-0.043	-0.012	0.626	1.574	-0.023	-0.007	-0.075
	Forest ecological space	0.384	0.314	0.158	3.360	-13.91	0.344	0.551	-0.203
	Grassland ecological space	0.045	-0.012	-0.033	-0.710	0.056	-0.033	0.019	-0.280
	Water ecological space	-0.002	0.060	-0.028	0.539	-0.142	0.000	-0.044	-0.121
	Other ecological spaces	0.000	0.002	-0.003	0.016	0.043	-0.002	-0.002	-0.005
	Agricultural production space	-0.301	-0.551	-0.013	-6.364	5.143	-0.191	-0.448	1.449
	Industrial production space	-0.024	-0.081	-0.008	0.346	0.623	-0.003	-0.021	-0.044
	Urban living space	-0.106	-0.291	-0.061	2.112	6.758	0.041	-0.038	-2.406
2020	Rural living space	-0.001	-0.059	-0.007	1.461	1.575	-0.021	-0.009	-0.151
	Forest ecological space	0.409	0.726	0.126	4.707	-16.17	0.161	0.561	0.653
	Grassland ecological space	0.056	-0.002	-0.023	-1.960	0.604	-0.006	0.012	-0.095
	Water ecological space	-0.009	0.112	-0.021	-0.546	0.269	-0.003	-0.043	-0.152
	Other ecological spaces	0.000	0.001	-0.001	0.010	0.045	-0.001	-0.002	0.001

The evolution of the spatial pattern of agricultural production was affected by factors with significant spatial and temporal heterogeneity (Figure 6). The influence of each factor on the spatial quantitative changes in agricultural production created both positive and negative spatial distributions. Factor X3 was mainly positively related to the spatial relationship of agricultural production on the Indochina Peninsula, but negatively related to the spatial relationship of agricultural production in southern Myanmar, northwestern Thailand, and northern Laos; the positive feedback expanded northward over time. In 2020, factor X2 showed a large area of negative feedback; in 2010, however, there had been positive feedback in the cities of northern and southern Vietnam. By 2020, positive feedback was only evident in the cities of northern Vietnam. In 2010, factor X1 had an inverse effect on the spatial quantity change in agricultural production; in that year, it was distributed in the south of Laos and the center of Vietnam; by 2020, it had spread southward to the central and southern cities of Laos and Vietnam. For factor X5, there was little change in the distribution areas of the positive and negative effects; the negative feedback areas were distributed in the south of Myanmar, Cambodia, and Thailand, as well as in Vietnam. Factor X6 demonstrated a negative feedback area distributed in the center of Thailand, Myanmar, Vietnam, Laos, and the northern region of Cambodia. The positive feedback area grew from 2010 to 2020, and was focused on the central region of the Indochina Peninsula. Factor X8 changes show a decreasing trend in the negative feedback areas, with decreasing areas concentrated in Vietnam and southern Thailand; the negative feedback area in central and northern Myanmar remains almost unchanged. The negative feedback area for the nighttime lighting factor decreased, with the area in northern Myanmar and Laos decreasing, and the negative feedback area in Cambodia moving to the south. The negative feedback area for factor X7 was larger in size, and the positive feedback area was concentrated in

northern Myanmar, the distribution area of negative feedback gradually decreasing in the period from 2010 to 2020.
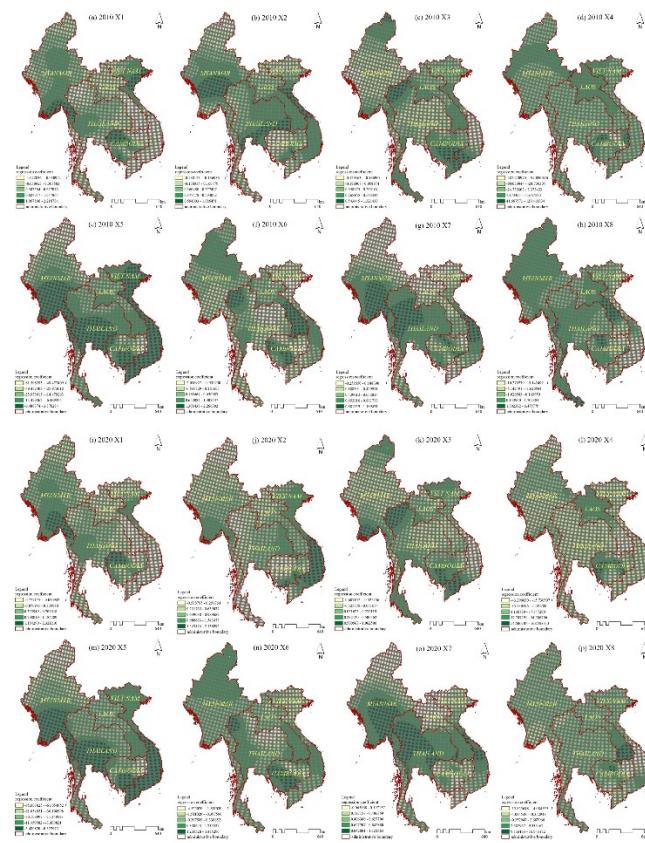
Figure 6. Spatio-temporal distribution of the effects of factors on agricultural production space. (a-p) represents the influence degree of different factors on the evolution of different land use space in different periods.

Factor X1 was mainly positively related to the forest ecological space; the negative feedback areas for this factor decreased with time, the decreased areas being concentrated in the northern region of Thailand and on the border of Myanmar (Figure 7). Factor X3 was mainly positively related to the ecological space of the forest land; the negative feedback areas for factor X3 were concentrated in the central region of Myanmar and the eastern region of Thailand, and decreased to the northeast with the change over time. Factor X2 experienced a decrease in negative feedback areas with the change over time. In 2020, the negative feedback areas for factor X2 were mainly in Cambodia's Battambang Province and Siem Reap Province, and Thailand's Surat Thani. The factor X5 positive feedback areas shifted from the provinces of Kandal and Takeo in Cambodia to Bangkok in Thailand. The negative feedback areas related to factor X6 spread out in all directions, and the positive feedback areas were concentrated on the Indochina Peninsula, rather than the center. Positive feedback areas for factor X8 were to the west of the Indochina Peninsula, while negative feedback areas were to the east. The negative feedback areas for this factor spread from the southeast to the northwest, being concentrated in the southern region of Myanmar. Factor X4 positive feedback areas were larger, and negative feedback areas expanded northwards. Positive feedback areas for factor X7 expanded northwards, and negative feedback areas were concentrated in the southern region of Laos. Factor X8 positive feedback areas spread northwards, while negative feedback areas were concentrated in the southern region of Laos. Positive feedback areas for factor X9 spread northwards. The negative feedback regions were concentrated in Phôngsali, Laos and the southern region of Burma.
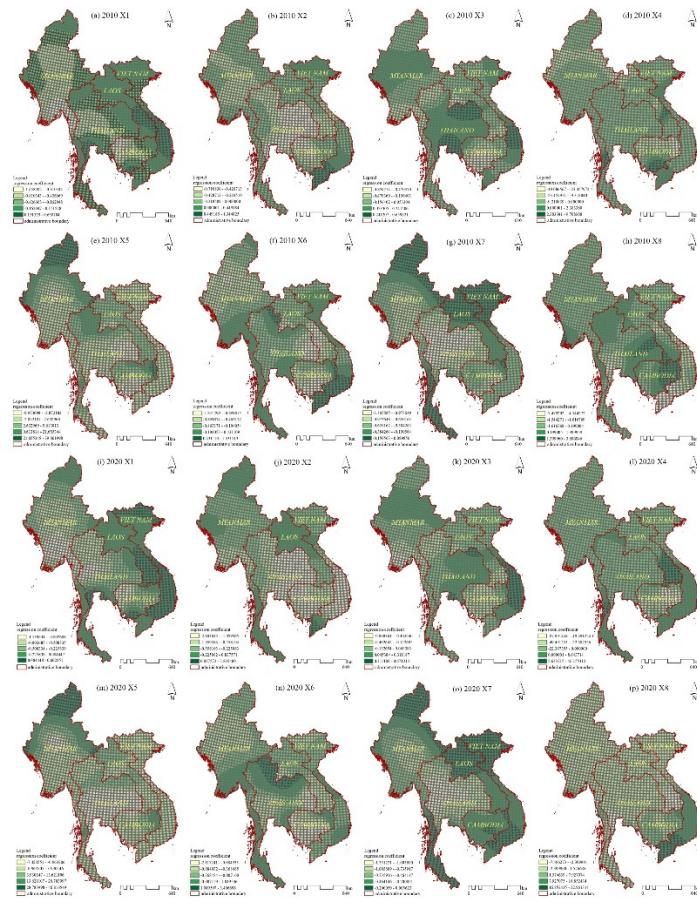
Figure 7. Spatio-temporal distribution of the effects of factors on forest ecological space. (a-p) represents the influence degree of different factors on the evolution of different land use space in different periods.

Factor X1 led to a large change in the positive feedback area for industrial production space; this mainly occurred in Thailand, with a decrease in the distribution in the northwest and a concentration in the east (Figure A1). The change resulting from X2 was a decrease in the positive feedback areas in the central region of Vietnam and the western region of Thailand. The changes in the distribution of the X3 factor were a shift in the positive feedback area from the periphery to the middle of the Indochina Peninsula and a decrease in the northern region of the positive feedback area in Vietnam. The change resulting from factor X4 was the 2020 conversion of negative feedback to positive feedback in northern Myanmar, northern Thailand, and southern Yunnan. The changes in factor X5 were the shrinkage of positive feedback in Myanmar and Thailand to the northeast, and the expansion of positive feedback in Cambodia to the west. The change resulting from factor X6 was the expansion of positive feedback to the south. The changes created by factor X7 were the shrinkage of positive feedback in northern Myanmar, the expansion of positive feedback to the north in Thailand, and the addition of positive feedback in southern Vietnam. The change created by factor X8 demonstrates that the positive feedback areas spread from the center to the east and west.

In Myanmar and Cambodia, the influence of X1 on the negative feedback of grassland ecological space changed greatly. Distribution in Myanmar changed from the central region to the western and eastern regions, while the negative feedback area in the eastern region of Cambodia decreased (Figure A2). The change brought by the X2 factor was that the negative feedback region spread from the central region to the surrounding region. By 2020, the spatial change created by X3 was that a new positive feedback area was added in the southern region of Laos, while the change wrought by X4 was that the negative feedback region expanded to the eastern region of the country. In 2020, positive feedback areas on grassland ecological space for factor X5 were mainly concentrated in northeast

Myanmar and Laos, and positive feedback areas appeared in northern Cambodia. The change resulting from factor X6 was that positive feedback areas developed from discrete to clustered in Cambodia and Laos, while the change created by X7 was that positive feedback areas spread from the perimeter to the center. By 2020, the change brought by X8 was positive feedback areas appearing in southern Myanmar and northern Vietnam.

In terms of rural living space, positive feedback areas for factor X1 all increased on the Indochina Peninsula (Figure A3). The change resulting from factor X2 was that positive feedback areas in Thailand expanded to the northeast, while the change created by factor X3 was that positive feedback areas expanded to the northwest. For factor X4, the change was that positive feedback areas expanded to the northeast. The factor X5 change was that negative feedback areas in Thailand expanded in a fan shape to the northeast; for factor X6, negative feedback areas in northern Vietnam converted to positive feedback areas. For factor X7, the change was that positive feedback areas in northern Thailand converted to negative feedback areas. For factor X8, the change was that negative feedback areas in northern Vietnam changed to positive feedback areas in northern Thailand. The change was that the negative feedback region in northern Vietnam converted to a positive feedback region, while, in northern Thailand, it was the positive feedback region that changed to a negative feedback region. The X7 change was that the positive feedback region in Myanmar expanded to the south, while the positive feedback region in Thailand decreased to the south. The X8 change was larger, with the positive feedback regions in Myanmar and Laos shifting to the northeast, and the positive feedback region in Vietnam disappearing.

In 2010, positive feedback for X1 on urban living space was distributed in Thailand, northern Vietnam, and central Laos, and by 2020, also in Cambodia (Figure A4). Factor X2 still resulted in negative feedback, although negative feedback in Myanmar and Cambodia had weakened. The change resulting from X3 was that the negative feedback areas in northern Thailand and central Laos converted to positive feedback, and the change created by X4 was that the negative feedback areas in northern Laos and Cambodia also converted to positive feedback. Factor X5 did not create significant change, with all areas still showing positive feedback. Factor X6 caused change as the positive feedback areas in Thailand decreased to the northeast. The positive feedback areas in the southern cities of Vietnam expanded to the northeast. The change caused by factor X7 was that the positive feedback area in Vietnam spread from the center to the north and south, while that caused by factor X8 was that the positive feedback area spread to the center.

In terms of the watershed ecological space, the X1 positive feedback influence expanded from the northeast to the southwest (Figure A5). The changes related to the X2 factor were that the negative feedback area in Myanmar spread to the east, while the positive feedback area in Thailand expanded to the west. For X3, the positive feedback area expanded to the east. The change associated with factor X4 was that the positive feedback area in Myanmar transformed from dispersed in the surroundings to clustered in the center, while the change in Cambodia and Myanmar was the opposite. For factor X5, the change was that the positive feedback area spread to the southwest. One X6 factor change was that the negative feedback areas in Myanmar and Laos spread to the north. The other X6 factor change for these countries was that the positive feedback regions in Myanmar and Laos also expanded to the north.   For factor X7, the change was that the positive feedback area narrowed downward to the north. The X8 factor negative feedback region spread to the southwest of Myanmar and Thailand.

Regarding other ecological space, the X1 impact was on the expansion of the positive feedback area in Thailand in 2020 (Figure A6). The changes associated with X3 were the spread of the positive feedback area in Myanmar to the north, and the expansion of the positive feedback area in Vietnam to the south. The changes brought by X4 were the conversion of positive feedback to negative feedback in the south of Vietnam, and the change from the negative feedback area to a positive feedback area in the north; the positive feedback area in Myanmar spread to the south. For X5, the positive feedback area in Cambodia disappeared, and the positive feedback areas in Myanmar were concentrated in the center. The X6 positive feedback area spread to the southwest, with the X6 positive feedback region spreading to the south. The X7 positive feedback region spread to the

southwest. The X8 positive feedback region expanded from the north of Myanmar and the south of Laos to the south, while the negative feedback region in Thailand converted to a positive feedback region.

4. Discussion

This study focused on the evolution of spatial and temporal patterns of PLES on the Indochina Peninsula from 2010 to 2020. It explored the developmental changes in human–land relations, analyzed the driving mechanisms of PLES changes, considered the spatial and temporal non-stationarity of the driving factors, and portrayed the spatial and temporal distributions of, and changes in, the drivers. It, therefore, provides reference information for the land-use function of the Indochina Peninsula and provides new perspectives for the study of driving mechanisms and changes. The conclusions are as follows:

1. In 2010–2020, the Indochina Peninsula PLES pattern was dominated by ecological space. The areas of production and living spaces increased dramatically, and the area of ecological space decreased accordingly. The trends in change are in line with the characteristics of regional resources and economic development. There are spatial differences in the rate of change in PLES patterns across the Indochina Peninsula. Cambodia has the fastest rate of change in PLES pattern, followed by Laos; Myanmar has the slowest.

2. In 2010–2020, the Indochina Peninsula had an area of 212,818.70 km2 of interconversion of PLES utilization types; this was manifested in the conversion of ecological space to production space, and the interconversion of woodland ecological space and grassland ecological space. The interconversion of production space and ecological space was distributed in a net-like manner throughout the Indochina Peninsula, and the transfer of living space was distributed in a point-like manner.

3. The migration path of the center of gravity of PLES on the Indochina Peninsula demonstrates significant directional differences. In 2010–2020, production space migrated to the southwest, living space shifted to the northeast, ecological space shifted to the east, and the distribution of ecological space was clearly affected by Laos and Vietnam in the east of the Indochina Peninsula. Living space tended to shrink in all directions, showing a trend from discrete to agglomerated distribution, mainly concentrated in Thailand, Laos, and Vietnam.

4. The transfer of PLES functional types throughout the Indochina Peninsula was influenced by social context and regional environment, the degree of influence of each factor having significant spatial and temporal heterogeneity. The distribution areas of positive and negative feedback effects for each factor are different, as are the transfer directions.

In the actual development process, due to the changes in the complexity of PLES caused by multiple factors, factors such as regional investment level, government policies, and soil properties should be considered in the future to improve the parameters and make the GTWR model fit better.

Author Contributions: Conceptualization, C.C.; methodology, X.L.; software, S.L.; validation, S.L.; formal analysis, S.L.; investigation, Q.G.; resources, S.L. and Z.Z.; data curation, Z.Z.; and L.Y.; writing—original draft preparation, S.L.; writing—review and editing, C.C. and X.L.; visualization, S.L.; supervision, Y.L.; and Z.B.; project administration, C.C.; funding acquisition, M.H. and Z.Z. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement: All data included in this study are available upon request by contacting the corresponding author.

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

Appendix A
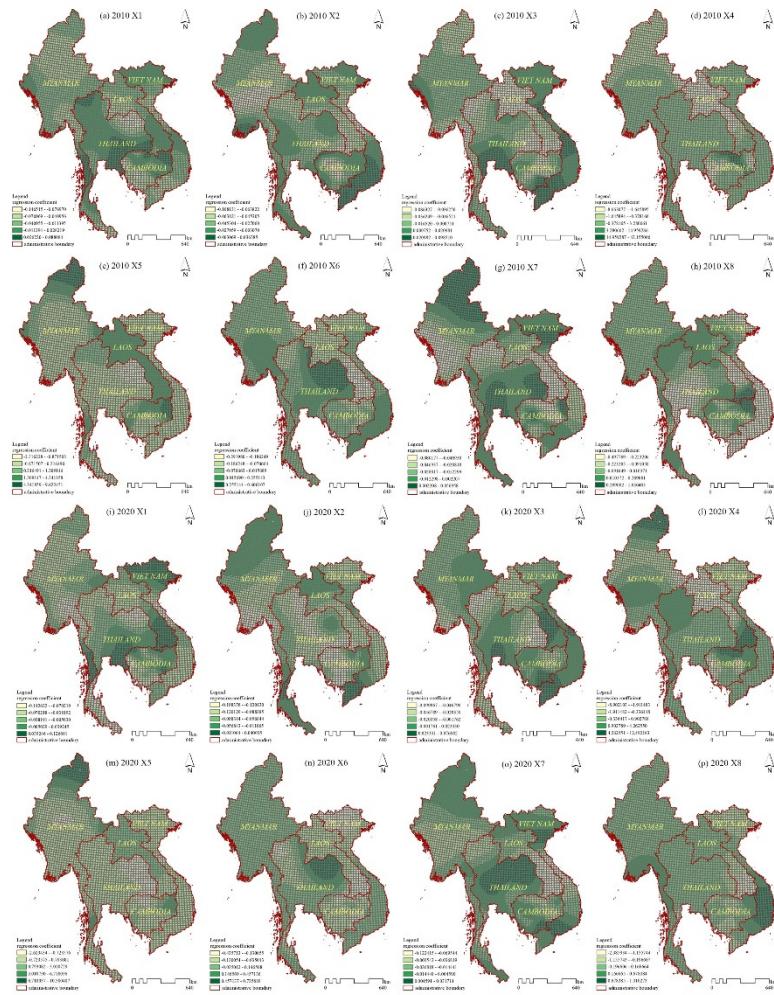
Figure A1. spatio-temporal distribution of the effects of factors on industrial production space.
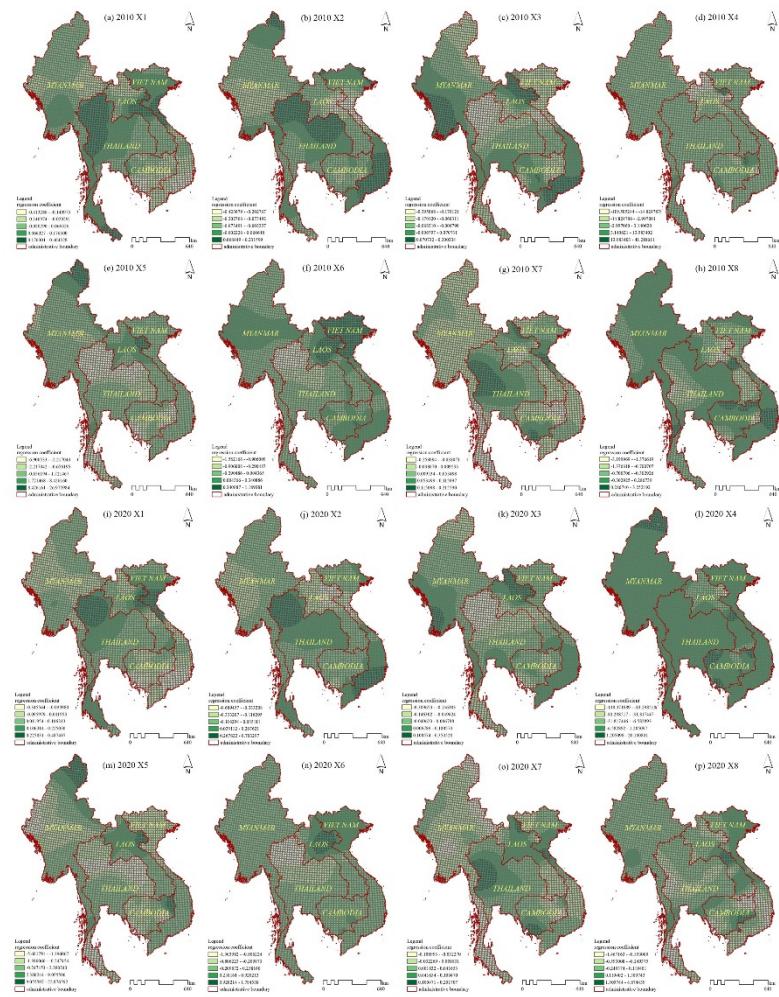
**Figure A2.** spatio-temporal distribution of the effects of factors on grassland ecological space.

**Figure A3.** spatio-temporal distribution of the effects of factors on rural living space.
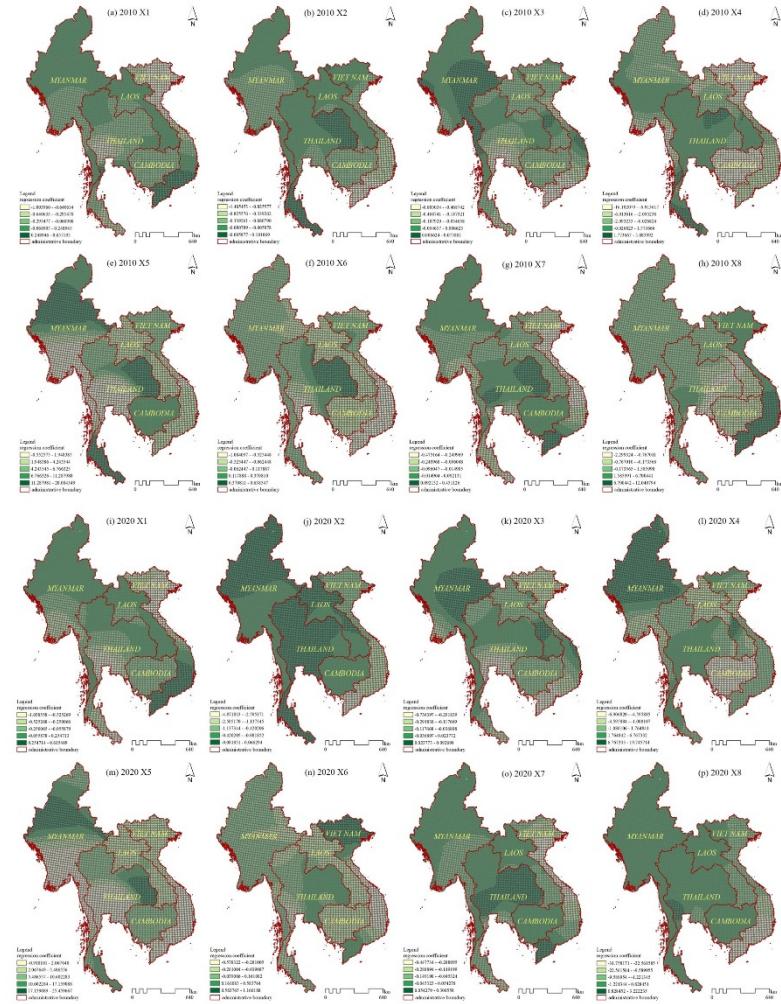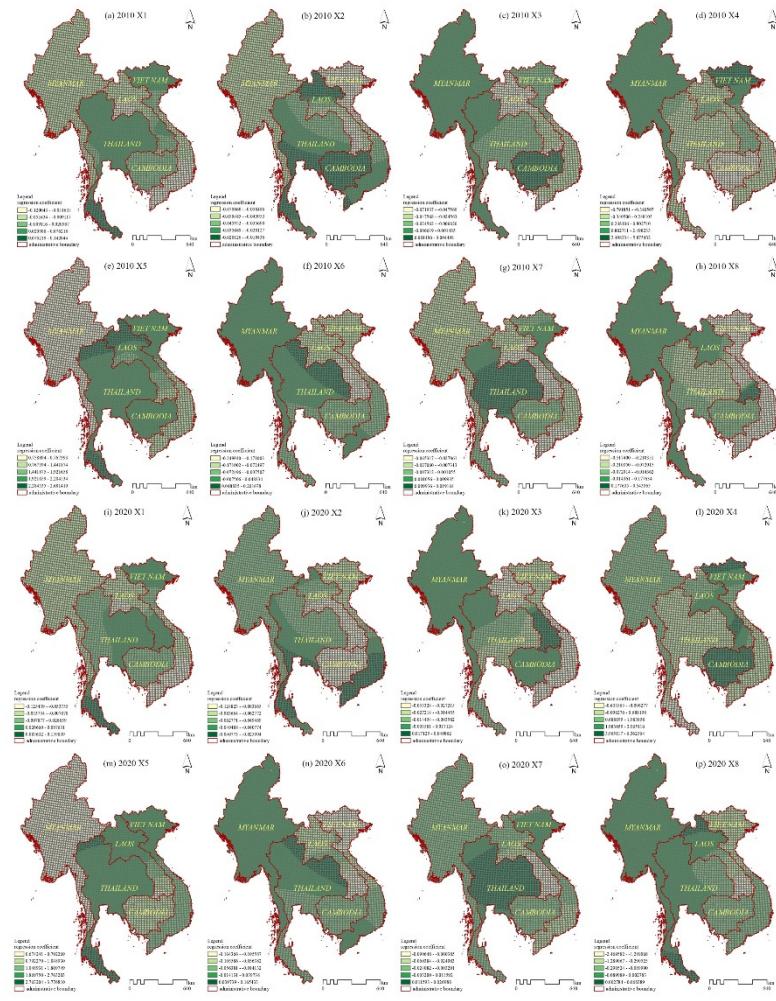
Figure A4. spatio-temporal distribution of the effects of factors on urban living space.
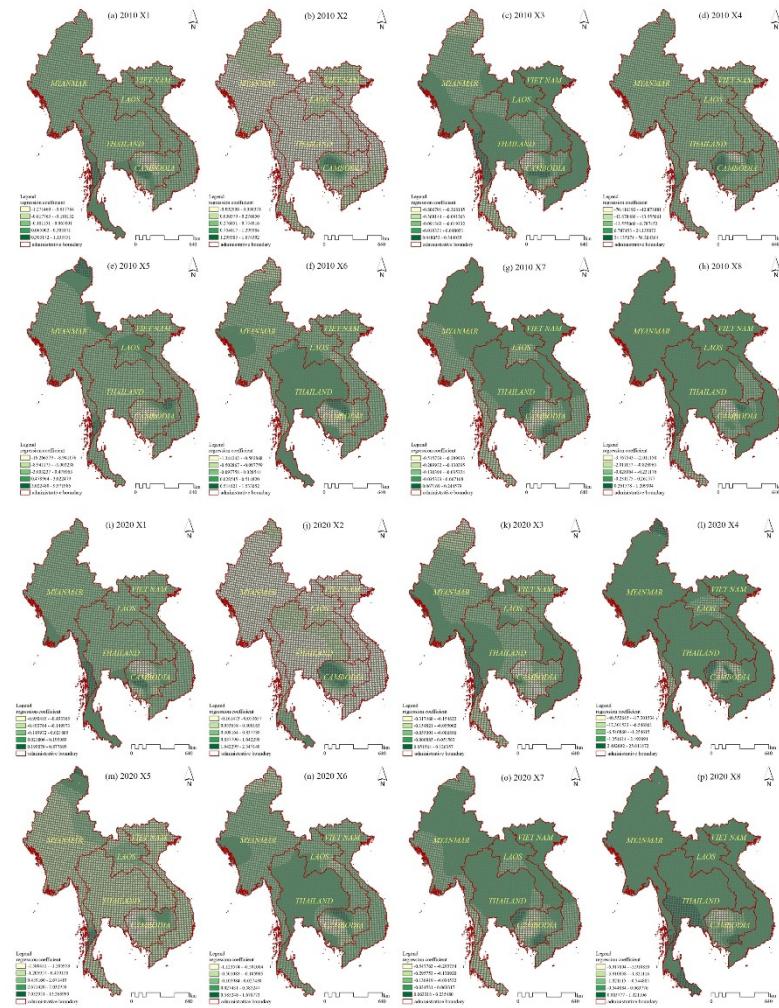
Figure A5. spatio-temporal distribution of the effects of factors on water ecological space.
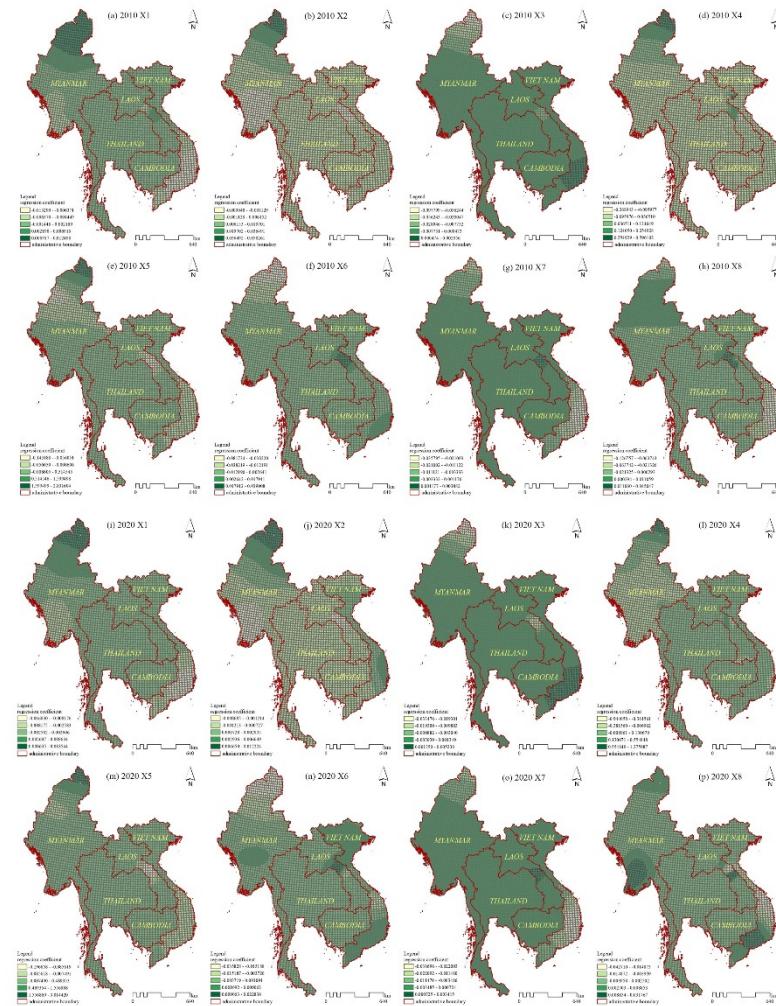
Figure A6. spatio-temporal distribution of the effects of factors on other ecological space.

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