

Article

Temporal and Spatial Evolution Characteristics and Its Driving Mechanism of Land Use/Cover in Vietnam from 2000 to 2020

Xiaoyu Niu ^{1,2,3}, Yunfeng Hu ^{1,2,*} , Zhongying Lei ³, Huimin Yan ^{1,2}, Junzhi Ye ^{1,2,4}  and Hao Wang ^{1,2}

¹ State Key Laboratory of Resources and Environmental Information System, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China; 202071354@yangtzeu.edu.cn (X.N.); yanhm@igsrr.ac.cn (H.Y.); yejunzhi999@nwafu.edu.cn (J.Y.); wangh.20s@igsrr.ac.cn (H.W.)

² College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China

³ School of Geosciences, Yangtze University, Wuhan 430100, China; leizhongying@yangtzeu.edu.cn

⁴ College of Natural Resources and Environment, Northwest A&F University, Xianyang 712100, China

* Correspondence: huyf@reis.ac.cn

Abstract: Research on the spatial distribution and dynamic evolution of land use/land cover (LULC) is the basis for land management and ecological protection. However, there is currently a lack of long-term analysis on the evolution of LULC on the national scale in Vietnam. Based on the GLC_FCS30 dataset, this paper analyzed the temporal and spatial evolution of LULC in Vietnam from 2000 to 2020 as well as its driving mechanism using methods such as dynamicity, flow direction diagrams, principal component analysis, and multivariate stepwise regression. The results show that: (1) cropland, forest, and shrubland are Vietnam's most important land-cover types. In 2020, the above three types of land area accounted for 34.77%, 32.36%, and 26.13% of the total land area, respectively. (2) From 2000 to 2020, the area of cropland and forest areas continued to shrink (−5.64%, −3.96%); the area of shrubland, water bodies, and other land areas expanded (+4.87%, +12.29%, +15.04%); and the area of impervious surfaces expansion was the most significant (+100.40%). (3) The integrated dynamic degree of LULC in Vietnam shows a spatial differentiation of high in the south, followed by the north, and lowest in the center. In the early period (2000–2010), the LULC rate of change in each region was rapid, while it gradually decreased in the later period (2010–2020). The most important LULC changes in Vietnam can be divided into two parts: (a) the mutual conversion of forest, cropland, and shrubland and (b) one-way conversion of cropland to impervious surfaces. (4) LULC changes in Vietnam are mainly affected by economic development and human activities, especially the GDP, population, and urbanization rate. There is no reliable statistical relationship between LULC and climatic factors. The results of this study contribute to the analysis of LULC processes in similar regions, and will also help the Vietnamese government strengthen national land management and planning in a targeted manner.

Keywords: land mapping; spatio-temporal pattern; correlation analysis; national development



Citation: Niu, X.; Hu, Y.; Lei, Z.; Yan, H.; Ye, J.; Wang, H. Temporal and Spatial Evolution Characteristics and Its Driving Mechanism of Land Use/Cover in Vietnam from 2000 to 2020. *Land* **2022**, *11*, 920. <https://doi.org/10.3390/land11060920>

Academic Editors: Christine Fürst, Hossein Azadi, Saskia Keesstra, Thomas Panagopoulos, Le Yu and Chuanrong Zhang

Received: 6 May 2022

Accepted: 14 June 2022

Published: 16 June 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Land is the most fundamental natural resource and material basis for human economic and social activities. Land-use/land-cover (LULC) change is a direct characterization signal through which various human production activities act on the earth's surface ecological environment [1,2]. LULC is related to many important issues, such as global climate and ecological environment change, the surface energy cycle, and human survival and development [3–5]. In the 1990s, the IGBP (the International Geosphere-Biosphere Programme) and IHDP (the International Human Dimensions Programme on Global Environmental Change) jointly launched the “LULC Change Scientific Research Program”. Moreover, the IGBP and IHDP launched the Global Land Program in 2005. In 2010, the United States held the first Open Science Conference on Global Land Program. In 2013, Verburg and other researchers

advocated for the establishment of land system science [6,7]. The implementation of these scientific programs, conferences, and initiatives has given scientists around the world and the public a new understanding of the theoretical significance and application value of LULC research.

Since the 1990s, many well-known institutions around the world have developed multiple sets of global land-cover products such as IGBP DISCover [8], GLC2000 [9], MODIS Collections 5 [10], GlobCover 2009 [11], etc. The early LULC products had a low spatial resolution and had no comparable datasets with continuous time-series; therefore, it is challenging to analyze finer time-series-based changes in LULC changes at small scales [12]. Since the 2000s, with the development of High-resolution Earth Observation Technology and remote sensing cloud computing technology, Chen et al. from the China National Basic Geographic Information Center produced GlobeLand30 products with 10-year intervals and a 30 m resolution from 2000 to 2020. The overall accuracy was over 80% [13]. Gong et al. of Tsinghua University produced FROM-GLC10 and FROM-GLC30 products with a 10 m/30 m resolution in 2015 and 2017, and their overall accuracies were 72.76% and 72.43%, respectively [14]. Liu et al. of the Chinese Academy of Sciences developed a five-year interval GLC_FCS30 (Global Land-Cover product with Fine Classification System) covering 30 land-cover types from 1985 to 2020, achieving an overall accuracy of 68.7% [15]. The Copernicus Global Land Service (CGLS) provided CGLS-LC100 at a 100 m resolution for 2015–2019, achieving an overall accuracy of over 80% [16]. Karra et al. developed the 2020 Esri 10 at 10 m resolution with an overall accuracy of 85% [17]. In addition, many scholars have conducted comparative studies on the accuracy of LULC products. Wang et al. compared the consistency of four high-resolution LULC products (LSV10, GLC_FCS30, ESRI10, and Globeland30) on the Indochina Peninsula. The results showed that the overall accuracy of the four LULC datasets was between 72% and 83% [18]. Armel et al. explored the consistency of GLC2000, GLOBCOVER, MODIS, and ECOCLI MAP on the African continent. The results showed that the consistency of the four LULC products was between 56% and 69% [19]. Hu et al. analyzed the consistency of GLOBCOVER2005, GLOBCOVER2009, GLC2000, and MODIS2000 on the European continent, and the results showed that the consistency of the four types of products was between 38.56% and 77.65% [20]. It is clear that the LULC products that have been released in recent years have shown huge improvements in spatial resolution, temporal continuity, and product accuracy of the datasets.

With the support of the above-mentioned LULC datasets, LULC research has continued to be developed and has included analyses of the spatio-temporal patterns in LULC change [21], discussions on the driving force mechanism of LULC change [22], the ecological effects of LULC changes [23], and the monitoring and modeling of LULC changes [24]. From the perspective of research scales, there have been many studies on the global, intercontinental, and transnational scales. For instance, Eric et al. [25] found that the global tropics reflect the trends of cropland, agricultural intensification, pasture expansion, tropical deforestation, and urban expansion and that these trends are driven by climate change, external policy interventions, the pressure of economic development and production on resource scarcity, the weak adaptive capacity of ecosystems, etc. Hu et al. [26] found that the area of cultivated land, forest land, shrubland, grassland, water bodies, and wetlands in Central Asia was increasing, while the area of bare land was decreasing. They also found that cultivated land expansion was influenced by human activities and precipitation; that urban expansion was influenced by population and economic development; and that natural vegetation changes were influenced by climate. In addition to the above-mentioned LULC studies at the intercontinental and transnational scales, studies at the national and regional scales remain critical. These studies at the national and regional scales could reveal the spatio-temporal patterns of local LULC changes in a more specific and profound way as well as reveal the effects of regional economic, social development, and climate change characteristics on LULC changes. These studies also could provide scientific information

for sustainable land development planning, ecological protection, etc., at national and regional levels.

Vietnam is a developing country located in Southeast Asia. Existing research is usually carried out on a smaller regional scale. Disperati et al. [27] studied the temporal and spatial changes in land use/cover in the Tam Giang-Cau Hai Lagoon area in central Vietnam from 1965 to 2014 based on AVHRR and Landsat satellite images using a computer visual interpretation method. Using the maximum likelihood method based on Landsat satellite images, Vu and Shen [28] conducted automatic land mapping in the Dong Trieu District from 2000 to 2019. In general, there is a lack of temporal and spatial analysis studies on LULC changes that have been conducted on a national scale in the Vietnam region. In addition, analyzing the driving mechanisms behind LULC changes in the region has been limited to qualitative analysis rather than quantitative statistical and model simulation. These deficiencies are due to the lack of well-established, reliable, and long-term LULC datasets.

In response to the existing problems in the previous LULC studies conducted in Vietnam, this paper selected the long-term, high-resolution GLC_FCS30 datasets and integrated critical national economic and social development data. Supported by the above data, our study attempts to analyze the spatio-temporal pattern and dynamic changes in Vietnam's LULC and explore the impact of regional climate, population, and economic development in Vietnam on its land-use/cover change processes. We attempt to answer the following three questions:

- (1) What are the spatio-temporal patterns of land use/cover in Vietnam during the period 2000–2020?
- (2) What are the main drivers of land-use/cover change in Vietnam from 2000 to 2020?
- (3) What are the uncertainties in the analysis of land-use/cover change in Vietnam?

2. Data and Methods

2.1. Study Area

Vietnam is located on the eastern coast of the Indo-China Peninsula in the southeast of the Asian continent (8°10'–23°24' N, 102°09'–109°30' E) and borders China to the north and Laos and Cambodia to the west. The territory of Vietnam is S-shaped and has a total area of about 3.3×10^5 km² (Figure 1). The whole of Vietnam is located south of the Tropic of Cancer and has a tropical monsoon climate and an average annual temperature of about 23°C. Vietnam has a distinct rainy and dry season, with the rainy season being from May to October and the dry season being from November to April of the following year. Due to the differences in latitude and topography, the annual precipitation in various regions of Vietnam ranges from 1200 mm to 3000 mm. In Vietnam, 90% of the precipitation occurs in the rainy season, and the annual average humidity reaches 84%.

The terrain of Vietnam is long and narrow, including the north, middle, and south regions of the country. The northern part of the country is mostly mountainous, with the altitude decreasing from west to east. The western terrain is steep, with an altitude of about 1500–2500 m, and is the highest area in the Indo-China Peninsula. Due to Red River souring, the northern plain is a flat triangular area that is known as the Red River Delta (RRD). The Annan Mountains, which stretch for more than 1200 km through the middle, constitute the backbone of Vietnam's terrain; Vietnam's largest plateau, the "West Highland" (WH), is located in the Annan Mountains. The Mekong Delta (MD) is in the south and has relatively stable terrain and a dense river network. It is the largest and most fertile plain in Vietnam.

The profile of the study area is cited in Socialist Republic of Vietnam Government Portal (<http://www2.chinhphu.vn/portal/page/portal/English/TheSocialistRepublicOfVietnam/AboutVietnam/AboutVietnamDetail?categoryId=10000103&articleId=10000505>, accessed on 3 June 2022).

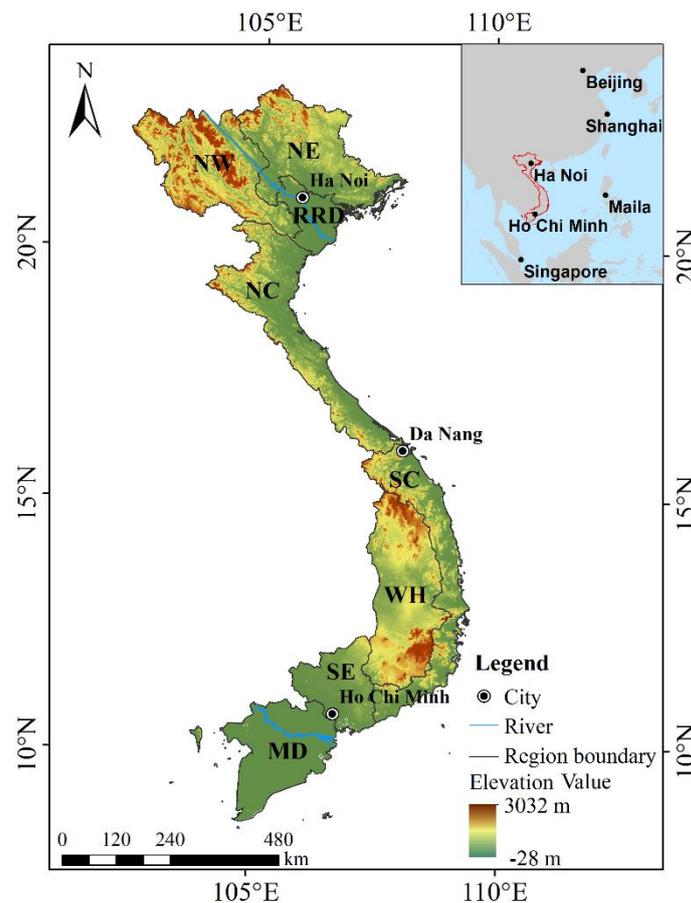


Figure 1. Location and topography map of Vietnam. NW: Northwest, NE: Northeast, RRD: Red River Delta, NC: North Central Coast, SC: South Central Coast, WH: West Highland, SE: Southeast, MD: Mekong River Delta.

2.2. Data Sources

The GLC_FCS30 dataset (2000, 2005, 2010, 2015, 2020) comes from the China Earth Big Data Science and Engineering Data Sharing Service System (https://data.cesearth.cn/sdo/list?searchKey=GLC_FCS30, accessed on 3 June 2022). This dataset was developed by Liu at the Institute of Aerospace Information Innovation, Chinese Academy of Sciences. The product contains nine first-level land-cover types and 30 s-level fine land-cover types. The overall accuracy of the first-level classification is 82.5% and the second-level accuracy is 68.7% [29]. According to the actual land distribution in the study area, this paper conducts research on the first-level land types, and the land types (grassland, wetlands) with very small areas are merged (Table 1). To be explained, impervious surface areas (ISAs) are defined as man-made land surface areas that water cannot pass through. They are primarily associated with human activities and habitation through the construction of transportation infrastructure and buildings [30].

Taking into account the need for monthly data accuracy and time horizon, the meteorological data (2000–2020 annual) are from the GLDAS-2.1 [31] and PERSIANN-CDR [32] datasets, both of which have a spatial resolution of 0.25 radians. Both the GLDAS-2.1 and PERSIANN-CDR datasets are global scales, with temporal resolutions of 3 h for GLDAS-2.1 and 1 day for PERSIANN-CDR. We used the Google Earth Engine to calculate the annual total rainfall, rainy season rainfall, and annual average temperature data for Vietnam. The economic and social statistics for 2000–2020 (annual) are from the Vietnam Statistics Office (<https://www.gso.gov.vn/>, accessed on 3 June 2022) and the World Bank (<https://data.worldbank.org.cn/country/vietnam?view=chart>, accessed on 3 June 2022).

Based on the Meteorological and economic statistics shown in Table 2, this paper aims to establish a system of drivers of LULC change in Vietnam.

Table 1. LULC classification system in Vietnam.

Code	Level 1 Classes	GLC_FCS30 LULC ID	Level 2 Classes of GLC_FCS30
1	Cropland	10	Rainfed cropland
		11	Herbaceous cover
		12	Tree or shrub cover (orchard)
		20	Irrigated cropland
2	Forest	51	Open evergreen broadleaved forest
		52	Closed evergreen broadleaved forest
		61	Open deciduous broadleaved forest (0.15 < fc < 0.4)
		62	Closed deciduous broadleaved forest (fc > 0.4)
		71	Open evergreen needle-leaved forest (0.15 < fc < 0.4)
		72	Closed evergreen needle-leaved forest (fc > 0.4)
3	Shrubland	120	Shrubland
		121	Evergreen shrubland
4	Impervious surfaces	190	Impervious surfaces
5	Water body	210	Water body
		220	Permanent ice and snow
6	Other	130	Grassland
		180	Wetlands

Table 2. Indicators and their categories of economic and social development statistics from 2000 to 2020.

Category	Index	Unit
Climate	X1 Total annual precipitation	mm
	X2 Rainy season precipitation	mm
	X3 Average annual temperature	°C
Social development	X4 Gross population	10,000 people
	X5 Rural population	10,000 people
	X6 Urban population	10,000 people
	X7 Urbanization rate	%
Economic development	X8 Gross Domestic Product (GDP)	100 million (current USD)
	X9 Agricultural value added	100 million (current USD)
	X10 Industrial value added	100 million (current USD)
	X11 Agricultural value added as a share of GDP	%
	X12 Industrial value added as a share of GDP	%
	X13 Cereal Production	kt
	X14 Aquaculture Production	kt
	X15 Fruit Production	kt
	X16 Export value of agricultural products	100 million (current USD)
	X17 Export value of forest products	100 million (current USD)
	X18 Export value of fish products	100 million (current USD)

Note: X1-X3 are from the GLDAS-2.1 and PERSIANN-CDR datasets; X14-X18 are from the Vietnam Statistics Office (<https://www.gso.gov.vn/>, accessed on 3 June 2022), and the rest of the indicator data are from the World Bank (<https://data.worldbank.org.cn/country/vietnam?view=chart>, accessed on 3 June 2022).

2.3. LULC Analysis Method

Integrated land-use dynamics are used to monitor the intensity of integrated land-use changes in the target zone [33]. Furthermore, it reflects an integrated impact of re-

gional human economic and social activities on LULC changes. The calculation method is as follows:

$$D = \left\{ \sum_{i=1}^6 \left(\frac{\Delta S_i}{S_i} \right) \right\} \times \frac{1}{T} \times 100\% \quad (1)$$

where D is the integrated land-use dynamic degree during the study time period; ΔS_i is the total area of LULC type i converted to other land types from the beginning of the study to the end of the study period; S_i is the total area of LULC type i at the beginning of the study; and T is the research period.

The single land-use dynamic degree is used to characterize the rate and magnitude of the change in a LULC type within a certain period of time [34]. The calculation method is as follows:

$$D_i = \frac{S_{i2} - S_{i1}}{S_{i1}} \times \frac{1}{T} \times 100\% \quad (2)$$

In the formula, D_i is the dynamic degree of the land-use/cover type at the study time; S_{i1} , S_{i2} denote the area of the land type i at the beginning and end of the study, respectively.

The land-use transition matrix is used to characterize the land-use change process. This matrix can reflect the land-use structure at the beginning and at the end of the study period and reveal the conversion rate and direction of each LULC type [35]. Using ArcGIS, we could spatially overlay the land-use data between the two periods. The overlaid data could be used to calculate the transition matrix of the LULC types in Vietnam. This matrix can reflect the conversion between various LULC types in Vietnam during the study period. In this paper, we have visualized the transition matrix. Its expression is:

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix} \quad (3)$$

where: S denotes the land area; i and j represent the LULC types at the beginning and end of the study period, respectively. n indicates the number of LULC types.

2.4. Analysis of Driving Mechanism

The traditional method correlates all of the drivers at once using a certain model and then identifies the key drivers affecting LULC change. The shortage of the method makes it difficult to eliminate the influence on the final results due to the existence of self-correlation between the driving factors [36].

Before conducting PCA (principal component analysis) and multiple linear stepwise regression analysis, it is necessary to perform a normality test. The normality test is used to check whether or not the data distribution is normal [37]. Normality testing can be conducted using the Shapiro–Wilk test, which uses a database that has not been processed in the frequency distribution table, and is limited to samples between 3 and 50 elements [38]. The significance test of the value of W with Shapiro–Wilk Table 2 can be seen in the probability value (p). Many authors consider the Shapiro–Wilk W statistic to be the best statistic for checking the data normality, especially for small sample sizes [39]. If $p > 0.05$, then the data is normally distributed. On the contrary, if $p < 0.05$, then the data are not normally distributed. Its formula is as follows:

$$W = \frac{\sum_{i=1}^m a_i (x_{n+1-i} - x_i)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (4)$$

where: a_i is a coefficient of the Shapiro–Wilk test (in our study, $a_1 = 0.6646$, $a_2 = 0.2413$), and x_i are values of the samples x_1, x_2, \dots, x_n (i.e., $x_1 \leq x_2 \leq \dots \leq x_n$). If n is even, let $m = n/2$, and if n is odd, let $m = (n - 1)/2$ (in our paper, $n = 5$, $m = 2$). \bar{x} is the average of the data.

This paper first carried out the PCA algorithm on 18 factors based on the SPSS platform to eliminate the internal correlation among the factors. The PCA algorithm projects a series of variables onto a few key factors, that is, it derives a few principal components from the original variables. The key factors retain as much information about the original variables as possible and demonstrate non-internal correlations. Thus, the PCA algorithm eliminates data redundancy. Then, regression models are constructed for each LULC change based on the key factors.

PCA is a statistical method for dimensionality reduction. The PCA process can be roughly summarized in two steps: The first step is to perform a linear transformation on a set of variables that may be internally correlated by using orthogonal transformation. The purpose of linear transformation is to transform a set of potentially correlated variables into a set of linearly uncorrelated variables. The second step is to recombine selected variables into a few uncorrelated comprehensive variables. These recombined variables are called principal components. Generally, we use the variance of F1 to indicate the information richness of F1. The larger the variance, the more information F1 contains. If F1 is not enough to express the information of many original indicators, then we consider selecting F2 as an additional indicator. Moreover, if the information already exists in F1, then it is not necessary to present the information in F2 nor in F3, F4...FP. Its construction formula is as follows:

$$F_p = A_{1i} * Z_{X1} + A_{2i} * Z_{X2} + \dots + A_{pi} * Z_{Xp} \quad (5)$$

where $A_{1i}, A_{2i}, \dots, A_{pi}$ are the eigenvectors corresponding to the eigenvalues of the covariance matrix of the variable X , and $Z_{X1}, Z_{X2}, \dots, Z_{Xp}$ are the values of the original variables after the Z standardization process.

LULC change is affected by many factors. In order to predict the dependent variable more effectively, this paper uses multiple linear stepwise regression to select the optimal combination from multiple independent variables. In this study, each land-use/cover type is the dependent variable. Additionally, climate, population, economic and social development, and other indicators are the independent variables. A multiple linear stepwise regression analysis is carried out with the support of the R language software platform. The multiple regression model is as follows:

$$Y = \beta + \alpha_1 X_1 + \alpha_2 X_2 + \dots + \alpha_n X_n \quad (6)$$

In the formula, $\alpha_1, \alpha_2, \dots, \alpha_n$ represent the correlation coefficient, β is a constant term, Y is the dependent variable, and X is the independent variable.

3. Results

3.1. Spatial Distribution

Statistics for various types of land areas in Vietnam in 2020 show that (Figure 2): in Vietnam, cropland (total area $11.46 \times 10^4 \text{ km}^2$, accounting for 34.77% of the area) and forest land ($10.67 \times 10^4 \text{ km}^2$, 32.36%) were the main land-cover types, followed by shrubland ($8.61 \times 10^4 \text{ km}^2$, 26.13%), impervious surfaces ($1.22 \times 10^4 \text{ km}^2$, 3.72%), water bodies ($0.81 \times 10^4 \text{ km}^2$, 2.45%), and other land types (grassland, wetlands) ($0.19 \times 10^4 \text{ km}^2$, 0.57%).

Nationally, cropland is widely distributed and is mainly concentrated in the two major plains of the Red River Delta in the north and the Mekong River Delta in the south, followed by the coastal region in the north-central and the south-central and the West Highland areas. Forest land and shrubland are mainly distributed in the mountainous areas of the Northwest, the Northeast, the North Central Coast, and the South-Central Coast. Impervious surfaces are scattered throughout the study area, with HoNoi and Ho Chi Minh being the most densely distributed. Water bodies are distributed in the Red River system in the northeast and the Mekong River basin in the south. The other land-cover type is distributed in the Northwest area, the eastern coast of the Ho Chi Minh City region, and the coastal area of the Mekong River Delta.

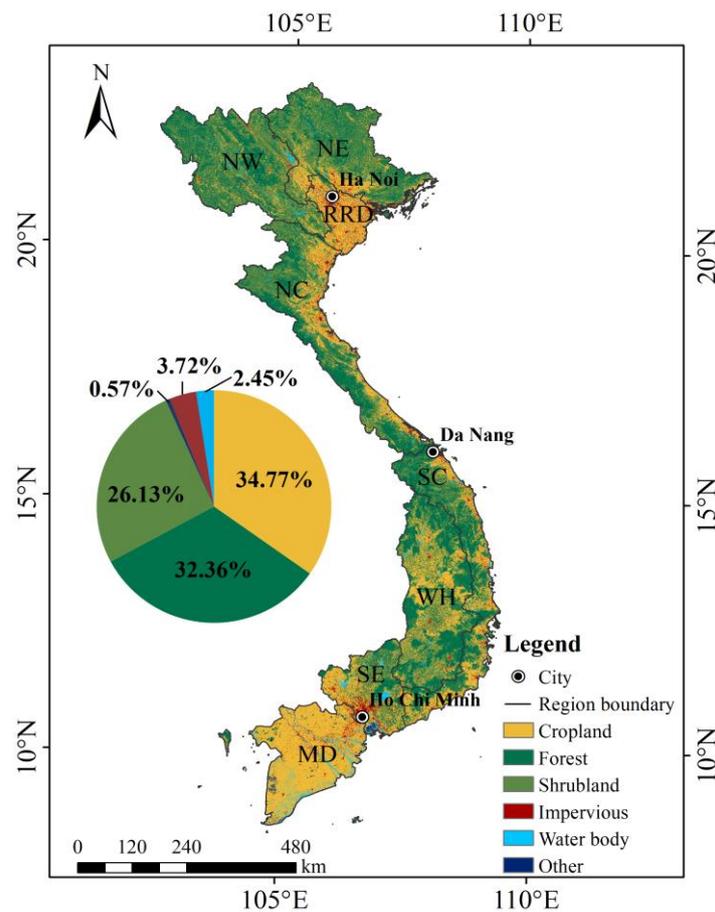


Figure 2. Land-use/land-cover map in 2020. NW: Northwest, NE: Northeast, RRD: Red River Delta, NC: North Central Coast, SC: South Central Coast, WH: West Highland, SE: Southeast, MD: Mekong River Delta.

From a regional perspective, the Northwest region of Vietnam was dominated by forest and shrubland, of which forest accounts for 41.8%, shrubland accounts for 41.7%, and cropland accounts for only 13.7%. Most Northeast areas comprise cropland, forest, and shrubland (21.3%, 33.8%, and 41.8%, respectively). The Red River Delta mainly consists of cropland and impervious surfaces, which account for 71.2% and 17.4% of the region's land area, respectively. The South-Central Coast mainly consists of cropland, forest, and shrubland (30.1%, 38.9%, and 24.7%, respectively). The West Highland is dominated by forest (47.5%) followed by cropland and shrubland (31.8%, 18.4%, respectively). The Southeast mainly consists of cropland (41.5%) followed by forest and shrubland, which account for 23.6% and 19.6% of the region's land area. Most of the Mekong River Delta area is cropland, which accounts for 84% of the land in the Mekong River Delta region.

3.2. Spatio-Temporal Dynamic Changes

From 2000 to 2020, the impervious surfaces throughout Vietnam expanded greatly, while the cropland and forest areas decreased. In the meantime, the area of shrubland, water bodies, and other land types have expanded to varying degrees. The impervious area changed significantly from $6.10 \times 10^3 \text{ km}^2$ to $12.21 \times 10^3 \text{ km}^2$ from 2000 to 2020. The absolute growth is $6.11 \times 10^3 \text{ km}^2$, showing a relative increase of 100%. The cropland and forest area decreased sharply ($-6.86 \times 10^3 \text{ km}^2$, $-4.40 \times 10^3 \text{ km}^2$, respectively), decreasing by 5.56% and 3.96%, respectively. The shrubland area increased by $4 \times 10^3 \text{ km}^2$ or by about 4.87%; the water body and other land areas increased little ($+0.89 \times 10^3 \text{ km}^2$, $+0.25 \times 10^3 \text{ km}^2$, respectively), but the growth rate was more significant (+12.29%, +15.04%, respectively) due to their smaller relative areas.

In terms of the change in dynamic degree, the rate of LULC change increased rapidly in the early period (2000–2010) and decreased rapidly in the later period (2010–2020). In 2000–2005 and 2005–2010, the integrated dynamic degree of LULC in Vietnam was 7.52% and 6.43%, respectively. The integrated dynamic degree of LULC in Vietnam gradually decreased to 5.87% and 5.53% in 2010–2015 and 2015–2020, respectively. There are significant differences in the integrated dynamic degree in northern, central, and southern Vietnam, and the highest was in the south, followed by the north, and the lowest was in the middle (Figure 3). From 2000 to 2005 (Figure 3A), the Mekong River Delta and the Southeast regions demonstrate the most active land change, showing integrated dynamic degrees of 14.10% and 13.96%, respectively, mainly due to the decrease in cropland. This was followed by the West Highland (9.99%), whose land-use change was mainly due to the decrease in forest areas. The integrated dynamic degree of land use in other regions ranges from 6.27% to 8.91%. From 2005 to 2010 (Figure 3B), in addition to the increase in the integrated dynamic degree of land use in the West Highland region, it was as high as 13.53%, which was mainly due to the substantial reduction in forest areas. The integrated dynamic degree of land use in other regions showed an obvious downward trend (mostly between 5.19% and 8.41%, Southeast was 11.32%). From 2010 to 2015 (Figure 3C), with the exception of the Northwest region, which increased to 12.04%, the integrated dynamic degree in other regions continued to show a downward trend (mostly between 4.42% and 6.94%, while the West Highland was 11.03%). By 2015–2020 (Figure 3D), the integrated dynamic degree of land-use cover in each region was generally low, ranging from 3.35% to 8.47%. It is noteworthy that the degree of land-use change in the North Central Coast region was low from 2000 to 2020, and its integrated dynamic degree was between 2.28% and 4.42%. Land-use change in the North Central Coast region was mainly caused by reductions in cropland.

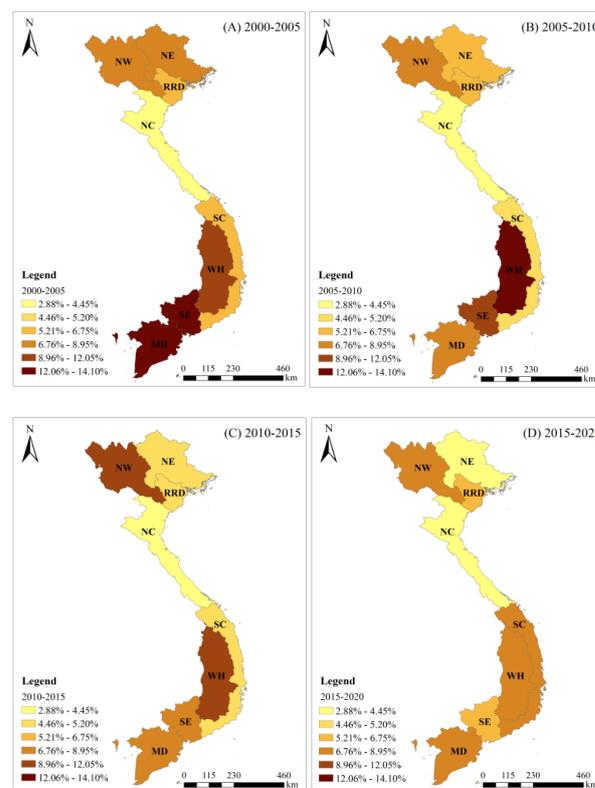


Figure 3. The spatial distribution map of integrated dynamic degree of LULC in Vietnam.

3.3. Source and Destination

By analyzing the area and composition of LULC change in Vietnam from 2000 to 2020 (Figure 4), we found that the conversion areas of all of the LULC types were 1.7×10^4 km² (5.16%) from 2000 to 2010, and 2.0×10^4 km² (6.07%) from 2010 to 2020. The most important LULC change processes in different periods are the interconversion among forest, cropland, and shrubland, and the one-way conversion of cropland to impervious surfaces. In addition, there are a few other LULC changes, such as the conversion of forest and shrubland to impervious surfaces, the interconversion between water body and cropland, etc.

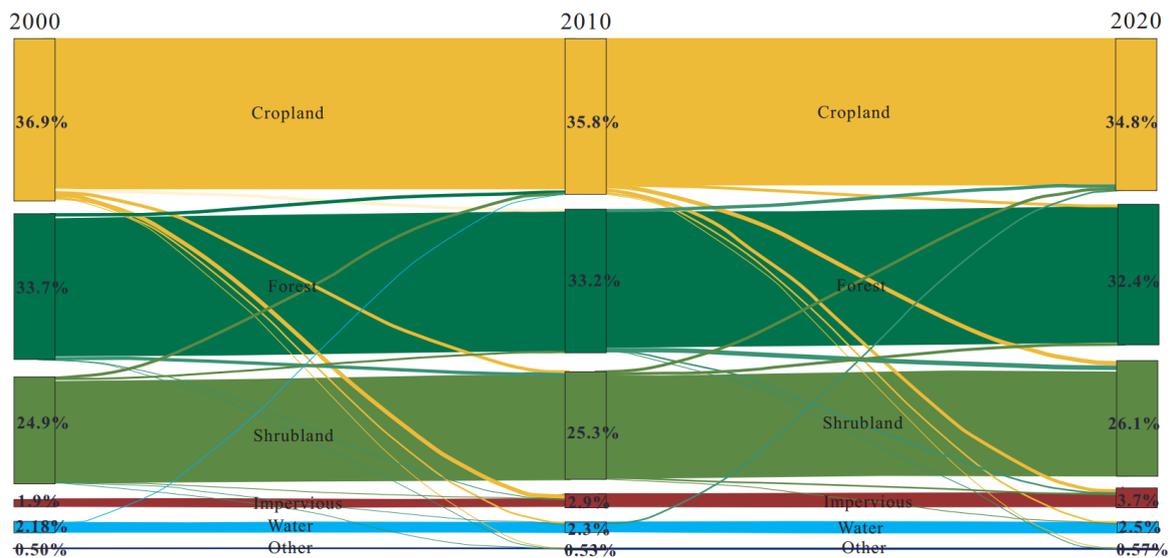


Figure 4. LULC transition plot in Vietnam during 2000–2020.

From 2000 to 2020, cropland decreased at an annual rate of about 0.28%, and the overall cropland showed a downward trend. The area of lost cropland totaled 14.73×10^3 km², which was mainly converted to forest land (21.69%), shrubland (34.09%), and impervious surfaces (36.07%), most of which were distributed in the Southeast and Red River Delta. Moreover, cropland area grew by 7.88×10^3 km², mainly from forest (55.04%) and shrubland (40.15%), mostly in the Southeast and West Highland, with little forest and shrubland being distributed in the North Central Coast and the South-Central Coast (Figure 5A).

The forest area also showed a decreasing trend, showing an integrated dynamic degree of LULC of -0.20% . In total, 10.79×10^3 km² of forest area was lost, mainly to cropland (40.20%) and shrubland (54.20%). During the same period, forest area increased by 6.39×10^3 km², mainly from cropland (50%) and shrubland (49.50%). The forest conversion process was mainly concentrated in the South-Central Coast, the West Highland region, and the Southeast (Figure 5B).

The integrated dynamic degree of shrubland was 0.24%, and the area continues to increase. In total, 6.90×10^3 km² of shrubland area was lost, mainly to cropland (45.84%) and forest (45.85%), most of which was mainly distributed in the North Central Coast, the South-Central Coast, the West Highland region, and the Southeast. Shrubland area increased to 10.90×10^3 km², mainly from cropland (46.06%) and forest (53.64%). These increases mainly occurred in the Southeast, the West Highland region, and the South-Central Coast (Figure 5C).

For impervious surfaces, the area gained was much larger than the area lost due to the effects of solid and continuous human activities. Furthermore, the process of impervious surface loss does not occur in some small-scale areas. In Vietnam, from 2000 to 2020, the integrated dynamic degree of impervious surfaces was as high as 5.02%. The net gain in the area of impervious surfaces was 6.12×10^3 km² and was mainly from cropland (86.81%);

some obvious change was concentrated in the Red River Delta, the West Highland region, and the Mekong River Delta (Figure 5D).

Water bodies showed a slight increasing trend, and their integrated dynamic degree was 0.61%. There was a decrease in the water body area of $0.45 \times 10^3 \text{ km}^2$, and this area was mainly converted to cropland (75.96%), mostly in the Mekong River Delta. During the same period, there was an increase in the area of $1.33 \times 10^3 \text{ km}^2$, mainly from cropland (73.39%), which occurred in all regions (Figure 5E).

The integrated dynamic degree of other land was 0.75%, and the area continued to increase. In addition, other land types (grassland and wetlands) only lost $0.07 \times 10^3 \text{ km}^2$ of their total area, mainly to cropland, and these losses were sporadically distributed in the Northwest region. During the same period, other land area types demonstrated a $0.31 \times 10^3 \text{ km}^2$ increase in their total area, mainly from cropland, mostly in the Mekong River Delta (Figure 5F).

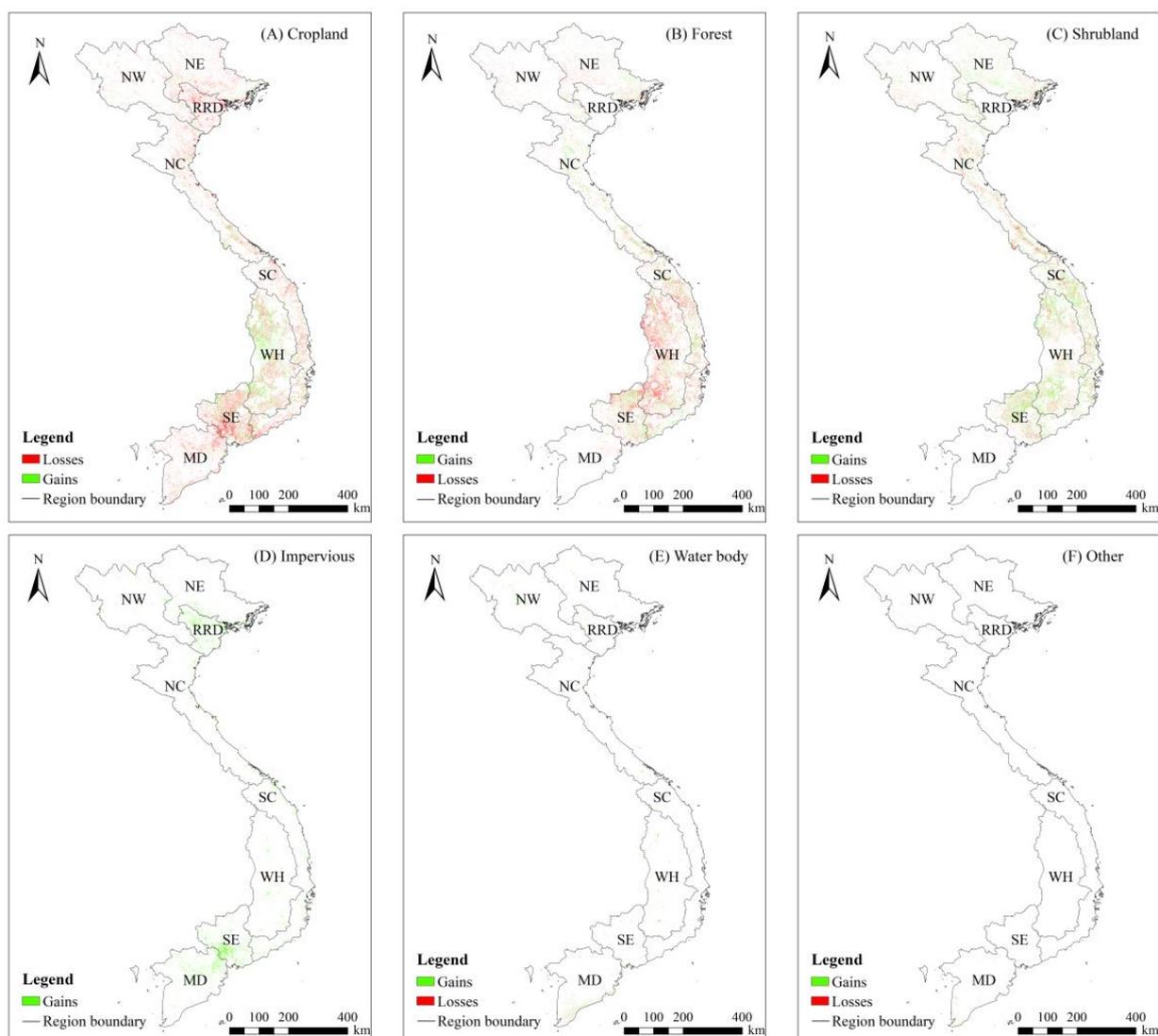


Figure 5. Spatial distributions of different LULC gains/losses during 2000–2020.

3.4. Economic, Social, and Climate Change

Based on the statistical indicators of Vietnam's economic and social development from 2000 to 2020 (annual) in Table 2, we analyzed the climate, economic, and social changes in Vietnam from 2000 to 2020. Additionally, we used the simple linear regression and

exponential regression (GDP, population growth rate) methods to calculate their trends, which made it easier to study the driving mechanism. The details are as follows:

From 2000 to 2020, Vietnam’s climate generally showed a slight warming and drying trend. For many years, the average annual temperature has been 23.1 °C and has shown an overall increasing trend (0.5 °C/10a) over the past 20 years. The change in the total precipitation in the rainy season from 2293.76 mm in 2000 to 2117.78 mm in 2020 is basically consistent with the total annual precipitation, which also shows a downward trend (Figure 6A).

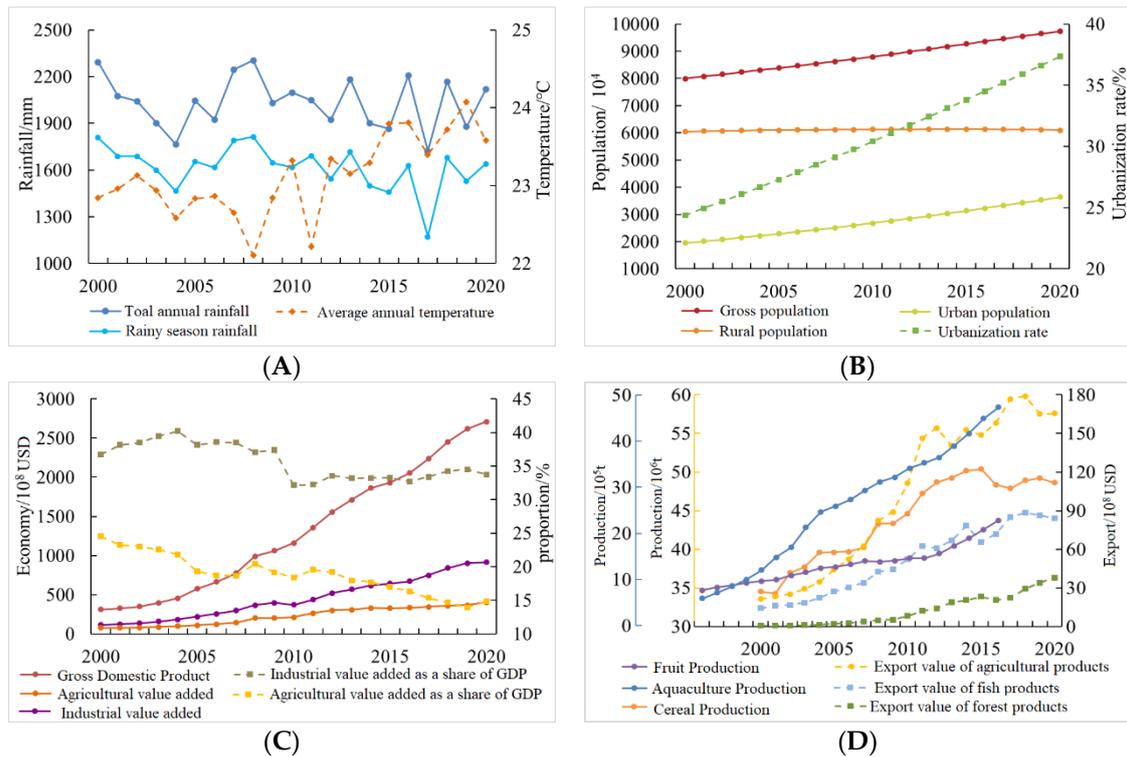


Figure 6. Development status in Vietnam from 2000 to 2020. (A) Climatic factors, (B) Population factors, (C) Economic factors, (D) Production and export factors.

The total population of the country is demonstrating a high growth trend. The annual growth rate of the country’s total population is 9.91‰, with a total increase of 17.43 million people in the past 20 years. Among them, the rural population has increased by 559,300, and the urban population has increased by 16,868,900. Urbanization is developing rapidly. The urbanization rate is steadily increasing, increasing from 24.6% in 2000 to 37.3% in 2020, with an annual increase of 6.3 percentage points (Figure 6B).

Vietnam’s national economy is developing rapidly. The average annual growth rate of the national GDP is 11.4%, from USD 31.173 billion in 2000 to USD 271.158 billion in 2020. The value-added from the primary industries and the value-added from secondary industries maintained the same rapid growth trend as the GDP. Due to the rapid development of tertiary industries, the proportion of the primary and secondary industries in the GDP shows a downward trend (Figure 6C).

From 2000 to 2020, the national grain output showed a rapid upward trend (8.2×10^5 t/a), from 3.5×10^7 t in 2000 to 4.8×10^7 t in 2020. Compared to grain output, the rising trend of fruit production and aquaculture production was more significant (annual growth rates of 6.3×10^4 t/a and 2.1×10^5 t/a), from 7.7×10^5 t and 5.9×10^5 t in 2000 to 22.8×10^5 t and 47.3×10^5 t in 2020. In addition to the obvious increase in material production, the value of the exports from agriculture, forestry, and aquaculture has also increased significantly. The average annual growth rate of the export value of agricul-

tural, forestry, and aquaculture products reached 9.2×10^8 USD/a, 1.8×10^8 USD/a, and 4.2×10^8 USD/a. Compared to 2000, the export value of agricultural, forestry, and aquaculture products in 2020 was 7.7 times, 60.9 times, and 5.9 times higher than before (Figure 6D).

3.5. Driving Forces and Driving Mechanisms of LULC

We calculated the *W* values of all of the independent variables using Formula (4), and the *p*-value was obtained by linear interpolation based on Table 2 of the Shapiro–Wilk Tables. For example, we calculated the *W* value of the total annual precipitation (X1) to be 0.966, and we then looked for a value of 0.966 when $n = 5$ in Table 2 of the Shapiro–Wilk Tables to determine whether the *p*-value lies between 0.50 ($W = 0.927$) and 0.90 ($W = 0.979$). Using the linear interpolation value of 0.966 between these values, we determined that the *p*-value is 0.80. Since the *p*-value = 0.80 > 0.05, we retain the hypothesis that X1 is normally distributed. According to this, we can conclude that all of the independent variables (X1–X18) in our study are normally distributed (Table 3). Since the *p*-value is based on linear interpolation, it is not very accurate, but the important thing is that it is much higher than 0.05, meaning that our normality test has a high degree of confidence.

Table 3. Normality test of independent variables.

Variables	Description	W-Value	<i>p</i> -Value	Shapiro-Wilk Tables 2 for $n = 5$	
				W	<i>p</i>
X1	Total annual precipitation	0.966	0.80		
X2	Rainy season precipitation	0.941	0.61	0.686	0.01
X3	Average annual temperature	0.895	0.39		
X4	Gross population	0.984	0.93	0.715	0.02
X5	Rural population	0.913	0.45		
X6	Urban population	0.980	0.92	0.762	0.05
X7	Urbanization rate	0.984	0.94		
X8	Gross Domestic Product (GDP)	0.946	0.65	0.806	0.1
X9	Agricultural value added	0.936	0.57		
X10	Industrial value added	0.946	0.65	0.927	0.5
X11	Agricultural value added as a share of GDP	0.937	0.58		
X12	Industrial value added as a share of GDP	0.914	0.46	0.979	0.9
X13	Cereal Production	0.948	0.66		
X14	Aquaculture Production	0.984	0.93	0.986	0.95
X15	Fruit Production	0.931	0.53		
X16	Export value of agricultural products	0.911	0.45	0.991	0.98
X17	Export value of forest products	0.884	0.36		
X18	Export value of fish products	0.968	0.82	0.993	0.99

Since the 18 factors in the statistic have different units of measurement, the magnitude of their values varies widely. We first standardized the data so that all of the variables had the same standard deviation. Then, PCA was performed in SPSS. The PCA showed that (Table 4) the information on the changes in the 18 indicators in Vietnam over the past 20 years can be summarized in two dimensions. The priority principal component, F1, is the economic and social development feature, which is highly positively correlated with 10 factors: the gross population (X4), urban population (X6), urbanization rate (X7), gross domestic product (X8), agricultural value-added (X9), industrial value-added (X10), cereal production (X13), aquaculture production (X14), export value of agricultural products (X16), and export value of fish products (X18). F2 is the climate change dimension and has a strong positive correlation with two factors: the total annual precipitation (X1) and rainy season precipitation (X2). In terms of the contribution of F1 and F2, the effect of F1 is much more significant than F2 (84.04% vs. 10.75%).

Table 4. Rotated component matrix of the PCA.

Variables	Description	Component	
		F1-Economic and Social Development	F2_Climate Change
X1	Total annual precipitation	−0.614	0.736
X2	Rainy season precipitation	−0.748	0.652
X3	Average annual temperature	0.933	−0.158
X4	Gross population	0.990	0.129
X5	Rural population	0.741	−0.633
X6	Urban population	0.984	0.166
X7	Urbanization rate	0.989	0.131
X8	Gross Domestic Product (GDP)	0.970	0.229
X9	Agricultural value added	0.986	0.142
X10	Industrial value added	0.963	0.243
X11	Agricultural value added as a share of GDP	−0.939	0.060
X12	Industrial value added as a share of GDP	−0.730	0.117
X13	Cereal Production	0.975	−0.222
X14	Aquaculture Production	0.989	0.133
X15	Fruit Production	0.913	0.382
X16	Export value of agricultural products	0.993	−0.001
X17	Export value of forest products	0.927	0.328
X18	Export value of fish products	0.991	0.114
	Variance (%)	84.04%	10.75%
	Eigenvalues	15.13	1.02

We took the area of various land-use types as the dependent variables and the two principal components as the independent variables. By applying the multiple linear stepwise regression method, we obtained the regression models of the area of each category with the principal components F1 (economic and social) and F2 (climate change) (Table 5). The results reveal that the cropland area was significantly negatively correlated with F1, which indicates that with the improvement of national economic and social development level in Vietnam, the cropland area in the country has decreased. In contrast, there was a significant positive correlation between F1 and the area of three land-cover types: impervious surfaces, shrubland, and water bodies. The positive correlation reveals that with the improvement of Vietnam's national economic and social development level, the area of impervious surfaces, shrubland, and water bodies will continue to increase accordingly. The forest area is negatively correlated to F1 and F2. This simultaneous correlation shows that with the improvement of Vietnam's national economic and social development level and the increase in precipitation, the forest area in the country will gradually decrease. In general, the changes in the major LULC types in Vietnam are mainly affected by economic and social development changes, while climate change only affects the forest area.

Table 5. Relationships between land-cover change and principal components in different types.

Cropland	$Y1 = 117862.5^{***} - 2651.8 \times F1^{**} - 211 \times F2$	$R^2 = 0.97, p < 0.05$
Impervious	$Y4 = 9290^{***} + 2409.6 \times F1^{***}$	$R^2 = 0.98, p < 0.001$
Shrubland	$Y3 = 83734.1^{***} + 1452.6 \times F1^{**} + 512.1 \times F2$	$R^2 = 0.97, p < 0.05$
Water	$Y5 = 7665.7^{***} + 370.3 \times F1^{***}$	$R^2 = 0.98, p < 0.001$
Forest	$Y2 = 109151.58^{***} - 1680.6 \times F1^{**} - 436.5 \times F2^*$	$R^2 = 0.99, p < 0.05$

Note: the significance test symbol * is $p < 0.05$, ** is $p < 0.01$, and *** is $p < 0.001$.

Furthermore, we used six land area types as dependent variables and the following twelve explanatory factors as input variables: X4, X6, X7, X8, X9, X10, X13, X14, X16, and X18 in F1 and X1 and X2 in F2. Then, we established the multiple linear regression models of the different land-use types (Table 6). This model indicated that the cropland area is significantly negatively correlated with the urban population (X6) and significantly posi-

tively correlated with GDP (X8). In addition, the impervious surface area has a significant positive correlation with the urbanization rate (X7) but a significant negative correlation with the urban population (X6). The water area has a significant positive relationship with aquaculture production (X14). There is no reliable statistical relationship between the forest and shrubland areas and the related economic, social, and climatic factors. The above results reveal that the main LULC type changes in Vietnam are mainly influenced by core economic and social development factors such as the GDP size, urban population size, and urbanization rate. Except for the water body area being directly related to aquaculture production, other industry development factors (physical quality factor, value quantity) have no plausible impact on LULC use. All of the climate change factors have no plausible impact on LULC change.

Table 6. Multivariate linear stepwise regression results of the area of land-use types and driving factors.

Cropland	$Y1 = 136200^{***} - 8.1 \times X6^{**} + 2.8 \times X8^*$	$R^2 = 0.99, p < 0.001$
Impervious	$Y4 = -15420^{**} - 8.2 \times X6^{**} + 1541 \times X7^{**}$	$R^2 = 0.99, p < 0.001$
Water	$Y5 = 8370.6^{**} - 0.7 \times X2 + 0.2 \times X14^*$	$R^2 = 0.97, p < 0.05$

Note: the significance test symbol * is $p < 0.05$, ** is $p < 0.01$, and *** is $p < 0.001$.

4. Discussion

4.1. Land Change and Its Impacts and Recommendations

In our study, from 2000 to 2020, Vietnam's cropland and forest area decreased, the area of impervious surfaces expanded significantly, and shrubland, water bodies, and other land types increased in area to varying degrees. This finding is consistent with regional-scale findings by Disperati [27] in central Vietnam, Tran [40] in the southern Mekong Delta, and Nguyen [41] in Ca Mau, etc. Their research also indicates that the cropland and forest area was shrinking, construction land area was expanding rapidly, and the area for aquaculture was increasing in Vietnam's leading economic regions. On the other hand, as a developing country located in the tropics and subtropics, Vietnam's LULC change trends are similar to those of other similar developing countries globally. Muhammad's [42] study of the Perak River Basin in Malaysia and the Ning et al. [43] study of China suggest that the typical mechanism of change in developing countries was that an area expansion of built-up land usually comes at the cost of a shrinking area of cropland and forest.

This paper pointed out that in the past 20 years, most of the net transfer of forest from Vietnam has become shrubland, while most of the net transfer of cropland has become impervious surfaces, and a small part of cropland has become water and wetlands. The changing LULC trend, that is, semi-artificial ecosystems turn into strong artificial intervention ecosystems, and high-productivity ecosystems turn into low-productivity ecosystems, is actually a process of indicating a deteriorating ecosystem structure. This deterioration process will further lead to a decline in Vietnam's national ecological services functions (especially ecosystem supply, water conservation, biodiversity energy, and food production, etc.). The above decline would further affect the stability of regional ecosystems and the sustainability of national economic and social development. Therefore, the Vietnamese government should learn from the experiences and lessons of other developing countries and learn from the advanced concepts and practices of ecological protection being implemented in developed countries. The Vietnamese government should also introduce legislation jobs covering aspects of land planning and management, such as national basic farmland protection [44], national forest park reserve system [45], and intensive urban construction [46], immediately.

4.2. Drivers of Land Change

Research on the driving mechanism of land-use/cover change at the global scale shows [47] that 60% of land-use/cover change can be attributed to human economic and social development activities and that 40% of LULC changes are related to factors such as climate change. However, our study shows that LULC change in Vietnam is

mainly affected by the country's economic and social development factors and is especially influenced by some crucial factors such as GDP, urban population, and the urbanization rate. Furthermore, climate change does not significantly influence LULC change in Vietnam. The reason for research differences is that Vietnam is in the tropical monsoon climate zone, and temperature or precipitation have never been the key factors restricting changes in the country's land surface ecosystem. In global-scale research, climate change factors will inevitably become the driving factors of LULC change since researchers need to consider those countries or regions located in arid or severe cold zones.

In fact, in Vietnam, the water bodies land-cover type is the most likely to be affected by climate change and also has no reliable statistical relationship with precipitation. In the past 20 years, the trends of climate change have demonstrated a continuous slight increase in temperature and that the total annual precipitation continues to decrease. However, to resist the impact of drought and to develop high value-added aquaculture, the government and the public have expanded the area dedicated to pond culture and water conservancy projects [48–50]. This paper also further reveals that there is a statistically positive relationship between changes in the water bodies area in Vietnam and the country's aquaculture production (not the value of aquatic product exports). Obviously, the expansion of water body areas will lead to an increase in fishery output. However, the increase in aquaculture output does not necessarily lead to an increase in the export revenue of aquatic products. The irrelevance of the aquaculture output value and export revenue of aquatic products may be because of the rising share of the domestic consumption of aquatic products and the fluctuation (decrease) in the international market price of aquatic products.

4.3. Uncertainty of the Study

The results of our study may still have uncertainties in some specific areas (such as mountains, and coastal zones) and some specific land-cover types (such as grasslands, shrubland, wetlands, etc.). Some scholars have pointed out that the GLC-FCS30 dataset is highly accurate for large-area, contiguous forests, and cropland. However, in the staggered areas of different land types and in areas with a particular type of terrain (mountains), the reliability of the dataset decreases sharply [51]. A fine-grained analysis by Linyucheva et al. in the Čiovo region of Vietnam also showed that the GLC-FCS30 dataset demonstrates more misclassification areas along the coastal zone area [52]. In addition, our study of the impervious surface area in Vietnam in this paper shows no transfer of impervious surfaces on the national scale in Vietnam, which is unreasonable for LULC timing change analysis at a 30 m resolution. As a developing country with rapid urbanization and modernization, although the area of impervious surfaces is increasing, a small number of impervious surfaces will be transformed into urban parks and green areas in some areas due to urban planning and urban renewal. Therefore, it is reasonable to consider that the developers of the GLC-FCS30 dataset may have experienced some misunderstandings when formulating the post-processing rules for the temporal changes of the impervious surfaces. The development of national-scale LULC products with specific classification systems is an important direction for future land mapping.

This study provides an effective technical method for analyzing the driving mechanism of LULC change. Our method first extracts the critical driving factors using principal component analysis and then establishes an association model by applying the multiple linear stepwise regression method. Our method is simple and provides a reference to similar research works in other countries and regions. However, it should be clearly pointed out that the linear regression modeling method based on correlation analysis is not an ideal method for judging the causal mechanism. The critical problem of the principal component analysis-multiple linear stepwise regression method is that the method on the driving mechanism of LULC change is based on the macro-scale. Furthermore, this method does not try to characterize or identify the spatial characteristics of the driving mechanism of LULC change. Moreover, this method attempts to simplify the complex,

nonlinear driving relationships to the univariate or multivariate linear relationships [53–56]. Applying and developing artificial intelligence modeling methods (Geospatial Artificial Intelligence, GeoAI) based on big data and spatial reasoning, as well as the study of spatial variability based on spatially fine-scale (regional, provincial administrative areas) may be the leading direction for understanding and characterizing the driving mechanism of LULC change [57,58].

5. Conclusions

Based on the global public LULC dataset and authoritative economic and social statistical data, this paper analyzed Vietnam's LULC change from 2000 to 2020 using dynamic degree, flow direction analysis, principal component analysis, and correlation analysis. The spatio-temporal patterns of the LULC change in Vietnam revealed the impact of economic and social development on LULC. Moreover, we also briefly discussed the potential impact of changes in LULC on national sustainable development and the uncertainty in research. Our research aims at the latest and longest time-series analysis of LULC variation patterns and mechanisms on a national scale.

Our research suggested that Vietnam's LULC types are dominated by cropland, forest, and shrubland. In the past 20 years, the area of Vietnam's cropland and forest area has decreased, while the shrubland, water body, and other land-use areas have shown an increasing trend, and impervious surface area has shown a high expansion trend. LULC changes in Vietnam are mainly influenced by human economic activities and have no statistical relationship with climate changes or fluctuations. The current LULC changes in Vietnam tend to be detrimental to the stability and sustainable development of the ecosystem, and the Vietnam government needs to pay attention and take targeted measures.

This paper established a LULC spatio-temporal evolution analysis method based on the GLC-FCS30 datasets. Simultaneously, we provide a driving mechanism analysis method based on principal components and multiple linear stepwise regression analysis. This technical route may be adapted to other countries and regions. However, this method also has some shortcomings, such as relying on the basic LULC data, and the driving factors of the modeling process have been over-simplified. For future work, on the one hand, we should improve the accuracy of the basic data. On the other hand, we need to focus on building artificial intelligence modeling methods (Geo-AI) based on big data and spatial reasoning to improve the credibility of the drive mechanism.

Author Contributions: Conceptualization, Y.H.; Methodology, Y.H.; Software, X.N., J.Y. and H.W.; Data curation, X.N.; Validation, X.N.; Investigation, J.Y.; Formal analysis, H.W.; Writing—original draft, X.N.; Writing—review and editing, Y.H. and H.Y.; Visualization, H.Y.; Supervision, Y.H. and Z.L.; Project administration, Y.H.; Funding acquisition, Y.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Natural Science Foundation of China (42130508), the Strategic Priority Research Program of the Chinese Academy of Sciences (XDA20010202), and the Network Security and Information Program of the Chinese Academy of Sciences (CAS-WX2021SF-0106).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Acknowledgments: The authors would like to express their sincere thanks to the anonymous reviewers because the comments and suggestions were of great help to improve the quality of this paper.

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

References

1. Perring, M.P.; De Frenne, P.; Baeten, L.; Maes, S.L.; Depauw, L.; Blondeel, H.; Carón, M.M.; Verheyen, K. Global environmental change effects on ecosystems: The importance of land-use legacies. *Glob. Chang. Biol.* **2016**, *22*, 1361–1371. [[CrossRef](#)] [[PubMed](#)]
2. Gueneralp, B.; Seto, K.C.; Ramachandran, M. Evidence of urban land teleconnections and impacts on hinterlands. *Curr. Opin. Environ. Sustain.* **2013**, *5*, 445–451. [[CrossRef](#)]

3. Liu, J.Y.; Deng, X.Z.; Liu, M.L.; Zhang, S.W. Study on the spatial patterns of land-use change and analyses of driving forces in Northeastern China during 1990–2000. *Chin. Geogr. Sci.* **2002**, *12*, 299–308. [\[CrossRef\]](#)
4. Sterling, S.M.; Ducharme, A.; Polcher, J. The impact of global land-cover change on the terrestrial water cycle. *Nat. Clim. Chang.* **2013**, *3*, 385–390. [\[CrossRef\]](#)
5. Boysen, L.R.; Brovkin, V.; Arora, V.K.; Cadule, P.; de Noblet-Ducoudré, N.; Kato, E.; Pongratz, J.; Gayler, V. Global and regional effects of land-use change on climate in 21st century simulations with interactive carbon cycle. *Earth Syst. Dyn.* **2014**, *5*, 309–319. [\[CrossRef\]](#)
6. Lambin, E.F.; Meyfroidt, P. Global land use change, economic globalization, and the looming land scarcity. *Proc. Natl. Acad. Sci. USA* **2011**, *108*, 3465–3472. [\[CrossRef\]](#)
7. Phv, A.; Nc, B.; Ece, C.; Ah, D.; Ph, E.; Om, F.; Hn, G.; Ts, H.; Khe, I.; Ng, J. Land system science and sustainable development of the earth system: A global land project perspective. *Anthropocene* **2015**, *12*, 29–41.
8. Loveland, T.R.; Reed, B.C.; Brown, J.F.; Ohlen, D.O.; Zhu, Z.; Yang, L.; Merchant, J.W. Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. *Int. J. Remote Sens.* **2000**, *21*, 1303–1330. [\[CrossRef\]](#)
9. Bartholome, E.; Belward, A.S. GLC2000: A new approach to global land cover mapping from Earth observation data. *Int. J. Remote Sens.* **2005**, *26*, 1959–1977. [\[CrossRef\]](#)
10. Friedl, M.A.; Sulla-Menashe, D.; Tan, B.; Schneider, A.; Ramankutty, N.; Sibley, A.; Huang, X. MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets. *Remote Sens. Environ.* **2010**, *114*, 168–182. [\[CrossRef\]](#)
11. Bicheron, P.; Defourny, P.; Brockmann, C.; Schouten, L.; Vancutsem, C.; Huc, M.; Bontemps, S.; Leroy, M.; Chard, F.A.; Herold, M. GlobCover—Products Description and Validation Report. *Mund. De La Salud* **2011**, *17*, 285–287.
12. Grekousis, G.; Mountrakis, G.; Kavouras, M. An overview of 21 global and 43 regional land-cover mapping products. *Int. J. Remote Sens.* **2015**, *36*, 5309–5335. [\[CrossRef\]](#)
13. Chen, J.; Liao, A.; Cao, X.; Chen, L.; Mills, J. Global land cover mapping at 30 m resolution: A POKbased operational approach. *ISPRS J. Photogramm. Remote Sens.* **2015**, *103*, 7–27. [\[CrossRef\]](#)
14. Gong, P.; Liu, H.; Zhang, M.; Li, C.; Wang, J.; Huang, H.; Clinton, N.; Ji, L.; Li, W.; Bai, Y.; et al. Stable classification with limited sample: Transferring a 30-m resolution sample set collected in 2015 to mapping 10-m resolution global land cover in 2017. *Sci. Bull.* **2019**, *64*, 370–373. [\[CrossRef\]](#)
15. Liu, L.; Zhang, X.; Gao, Y.; Chen, X.; Mi, J. Finer-Resolution Mapping of Global Land Cover: Recent Developments, Consistency Analysis, and Prospects. *Int. J. Remote Sens.* **2021**, *2021*, 5289697. [\[CrossRef\]](#)
16. Buchhorn, M.; Lesiv, M.; Tsendbazar, N.-E.; Herold, M.; Bertels, L.; Smets, B. Copernicus Global Land Cover Layers—Collection 2. *Remote Sens.* **2020**, *12*, 1044. [\[CrossRef\]](#)
17. Karra, K.; Kontgis, C.; Statman-Weil, Z.; Mazzariello, J.C.; Mathis, M.; Brumby, S.P. Global land use/land cover with Sentinel 2 and deep learning. In Proceedings of the 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, Brussels, Belgium, 11–16 July 2021; pp. 4704–4707.
18. Wang, H.; Yan, H.; Hu, Y.; Xi, Y.; Yang, Y. Consistency and Accuracy of Four High-Resolution LULC Datasets—Indochina Peninsula Case Study. *Land* **2022**, *11*, 758. [\[CrossRef\]](#)
19. Tchuenté, A.T.K.; Roujean, J.-L.; De Jong, S.M. Comparison and relative quality assessment of the GLC2000, GLOBCOVER, MODIS and ECOCLIMAP land cover data sets at the African continental scale. *Int. J. Appl. Earth Obs. Geoinf.* **2011**, *13*, 207–219. [\[CrossRef\]](#)
20. Hu, Y.; Zhang, Q.; Dai, Z.; Huang, M.; Yan, H. Agreement analysis of multi-sensor satellite remote sensing derived land cover products in the Europe Continent. *Geogr. Res.* **2015**, *34*, 1839–1852.
21. Fayaz, A.; Shafiq, M.U.; Singh, H.; Ahmed, P. Assessment of spatiotemporal changes in land use/land cover of North Kashmir Himalayas from 1992 to 2018. *Model. Earth Syst. Environ.* **2020**, *6*, 1189–1200. [\[CrossRef\]](#)
22. Li, Z.; Ren, Y.; Li, J.; Li, Y.; Rykov, P.; Chen, F.; Zhang, W. Land-Use/Cover Change and Driving Mechanism on the West Bank of Lake Baikal from 2005 to 2015—A Case Study of Irkutsk City. *Sustainability* **2018**, *10*, 2904. [\[CrossRef\]](#)
23. Hu, M.; Li, Z.; Wang, Y.; Jiao, M.; Li, M.; Xia, B. Spatio-temporal changes in ecosystem service value in response to land-use/cover changes in the Pearl River Delta. *Resour. Conserv. Recycl.* **2019**, *149*, 106–114. [\[CrossRef\]](#)
24. Parsa, V.A.; Salehi, E. Spatio-temporal analysis and simulation pattern of land use/cover changes, case study: Naghadeh, Iran. *J. Urban Manag.* **2016**, *5*, 43–51. [\[CrossRef\]](#)
25. Lambin, E.F.; Geist, H.J.; Lepers, E. Dynamics of land-use and land-cover change in tropical regions. *Annu. Rev. Environ. Res.* **2003**, *28*, 205–241. [\[CrossRef\]](#)
26. Hu, Y.; Hu, Y. Land Cover Changes and Their Driving Mechanisms in Central Asia from 2001 to 2017 Supported by Google Earth Engine. *Remote Sens.* **2019**, *11*, 554. [\[CrossRef\]](#)
27. Disperati, L.; Viridis, S. Assessment of land-use and land-cover changes from 1965 to 2014 in Tam Giang-Cau Hai Lagoon, central Vietnam. *Appl. Geogr.* **2015**, *58*, 48–64. [\[CrossRef\]](#)
28. Vu, T.T.; Yuan, S. Land-Use and Land-Cover Changes in Dong Trieu District, Vietnam, during Past Two Decades and Their Driving Forces. *Land* **2021**, *10*, 798. [\[CrossRef\]](#)
29. Zhang, X.; Liu, L.; Chen, X.; Gao, Y.; Mi, J. GLC_FCS30: Global land-cover product with fine classification system at 30 m using time-series Landsat imagery. *Earth Syst. Sci. Data* **2021**, *13*, 2753–2776. [\[CrossRef\]](#)

30. Lu, D.; Li, G.; Kuang, W.; Moran, E. Methods to extract impervious surface areas from satellite images. *Int. J. Digit. Earth* **2014**, *7*, 93–112. [[CrossRef](#)]
31. Rodell, M.; Kato, H.; Zaitchik, B. Ongoing Development of NASA's Global Land Data Assimilation System. In Proceedings of the 2008 American Geophysical Union Joint Assembly, Fort Lauderdale, FL, USA, 30 April 2008.
32. Ashouri, H.; Hsu, K.L.; Sorooshian, S.; Braithwaite, D.K.; Knapp, K.R.; Cecil, L.D.; Nelson, B.R.; Prat, O.P. PERSIANN-CDR: Daily Precipitation Climate Data Record from Multisatellite Observations for Hydrological and Climate Studies. *Bull. Am. Meteorol. Soc.* **2014**, *96*, 197–210. [[CrossRef](#)]
33. Pfaffenbichler, P.; Emberger, G.; Shepherd, S. The integrated dynamic land use and transport model MARS. *Netw. Spat. Econ.* **2008**, *8*, 183–200. [[CrossRef](#)]
34. Wang, S.; Liu, J.; Zhang, Z.; Zhou, Q.; Zhao, X. Analysis on spatial-temporal features of land use in China. *Acta Geogr. Sin.* **2001**, *56*, 631–639.
35. Mas, J.-F.; Velazquez, A.; Diaz-Gallegos, J.R.; Mayorga-Saucedo, R.; Alcantara, C.; Bocco, G.; Castro, R.; Fernandez, T.; Perez-Vega, A. Assessing land use/cover changes: A nationwide multivariate spatial database for Mexico. *Int. J. Appl. Earth Obs. Geoinf.* **2004**, *5*, 249–261. [[CrossRef](#)]
36. Ye, J.; Hu, Y.; Zhen, L.; Wang, H.; Zhang, Y. Analysis on Land-Use Change and Its Driving Mechanism in Xilingol, China, during 2000–2020 Using the Google Earth Engine. *Remote Sens.* **2021**, *13*, 5134. [[CrossRef](#)]
37. Ainiyah, N.; Deliar, A.; Virtriana, R. The classical assumption test to driving factors of land cover change in the development region of northern part of west Java. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2016**, *41*, 205. [[CrossRef](#)]
38. Shapiro, S.S.; Wilk, M.B. An analysis of variance test for normality (complete samples). *Biometrika* **1965**, *52*, 591–611. [[CrossRef](#)]
39. Hanusz, Z.; Tarasinska, J.; Zielinski, W. Shapiro-Wilk test with known mean. *REVSTAT-Stat. J.* **2016**, *14*, 89–100.
40. Hanh, T.; Thuc, T.; Matthieu, K. Dynamics of Land Cover/Land Use Changes in the Mekong Delta, 1973–2011: A Remote Sensing Analysis of the Tran Van Thoi District, Ca Mau Province, Vietnam. *Remote Sens.* **2015**, *7*, 2899–2925.
41. Nguyen, L.D.; Viet, P.B.; Minh, N.T.; Thy, P.T.M.; Phung, H.P. Change Detection of Land Use and Riverbank in Mekong Delta, Vietnam Using Time Series Remotely Sensed Data. *J. Resour. Ecol.* **2011**, *2*, 370–374.
42. Zeshan, M.T.; Mustafa, M.R.U.; Baig, M.F. Monitoring Land Use Changes and Their Future Prospects Using GIS and ANN-CA for Perak River Basin, Malaysia. *Water* **2021**, *13*, 2286. [[CrossRef](#)]
43. Jia, N.; Liu, J.; Kuang, W.; Xu, X.; Jing, N. Spatiotemporal patterns and characteristics of land-use change in China during 2010–2015. *J. Geogr. Sci.* **2018**, *28*, 547–562.
44. Eagle, A.J.; Eagle, D.; Stobbe, T.E.; Kooten, G. Farmland Protection and Agricultural Land Values at the Urban-Rural Fringe: British Columbia's Agricultural Land Reserve. *Am. J. Agric. Econ.* **2014**. *Online Access*. [[CrossRef](#)]
45. Харченко, Н.; Kharchenko, N.; Морковина, С.; Morkovina, S.; Skrynnikova, M. Methodical approach to the creation of a green forest park zone of the city agglomerations. *For. Eng. J.* **2017**, *7*, 122–133.
46. Hou, Y.; Hu, C.; Zang, X.; Tian, C. Thinking on the Intensive Use of Land in the Three-Dimensional City—Enlightening on Urban Construction in Hongkong. *Archit. Cult.* **2018**, *9*, 165–167.
47. Song, X.P.; Hansen, M.C.; Stehman, S.V.; Potapov, P.V.; Tyukavina, A.; Vermote, E.F.; Townshend, J.R. Global land change from 1982 to 2016. *Nature* **2018**, *560*, 639–643. [[CrossRef](#)]
48. Huynh, P.T.A.; Le, N.D.; Le, S.T.H.; Nguyen, H.X. Vulnerability of Fishery-Based Livelihoods to Climate Change in Coastal Communities in Central Vietnam. *Coast. Manag.* **2021**, *49*, 275–292. [[CrossRef](#)]
49. Qin, L.F. Research on the development of Vietnamese marine fishery. *Chin. Fish. Econ.* **2016**, *34*, 4–12.
50. Trinh, T.A.; Feeny, S.; Posso, A. The Impact of Natural Disasters and Climate Change on Agriculture: Findings from Vietnam. In *Economic Effects of Natural Disasters*; Academic Press: Cambridge, MA, USA, 2021.
51. Gao, Y.; Liu, L.; Zhang, X.; Chen, X.; Xie, S. Consistency Analysis and Accuracy Assessment of Three Global 30-m Land-Cover Products over the European Union using the LUCAS Dataset. *Remote Sens.* **2020**, *12*, 3479. [[CrossRef](#)]
52. Linyucheva, A.; Kindlmann, P. A review of global land cover maps in terms of their potential use for habitat suitability modelling. *Eur. J. Environ. Sci.* **2021**, *11*, 46–61. [[CrossRef](#)]
53. Lin, Y.; Deng, X.; Xing, L.I.; Enjun, M.A. Comparison of multinomial logistic regression and logistic regression: Which is more efficient in allocating land use? *Front. Earth Sci.* **2014**, *8*, 512–523. [[CrossRef](#)]
54. Hu, Y.; Gao, M. Evaluations of water yield and soil erosion in the Shaanxi-Gansu Loess Plateau under different land use and climate change scenarios. *Environ. Dev.* **2020**, *34*, 100488. [[CrossRef](#)]
55. Zondag, B.; Borsboom, J. Driving forces of land-use change. In Proceedings of the 49th ERS Conference, Lodz, Poland, 25–29 August 2009.
56. Lewis, M. Stepwise versus Hierarchical Regression: Pros and Cons. *Online Submiss* **2007**.
57. Pirasteh, S.; Zenner, E.K.; Mafi-Gholami, D.; Jaafari, A.; Kamari, A.N.; Liu, G.; Zhu, Q.; Li, J. Modeling mangrove responses to multi-decadal climate change and anthropogenic impacts using a long-term time series of satellite imagery. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *102*, 102390. [[CrossRef](#)]
58. Yu, Y.; Cao, Y.; Hou, D.; Disse, M.; Brieden, A.; Zhang, H.; Yu, R. The study of artificial intelligence for predicting land use changes in an arid ecosystem. *J. Geogr. Sci.* **2022**, *32*, 717–734. [[CrossRef](#)]