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Spatiotemporal Variations and Driving Factors of Ecological Land during Urbanization—A Case Study in the Yangtze River's Lower Reaches

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Abstract: Ecological land change is an important indicator of eco-environment quality when balancing urbanization and regional ecological safety. Nantong, located in the Yangtze River's lower reaches, has experienced rapid urbanization since the reform and opening-up policy was implemented in China in 1978. To ensure the regional ecological conservation and restoration of the Yangtze River and the city's sustainable development, we used remote sensing technology and statistical yearbook data as well as land use dynamic degree (LUDD) and Geodetector methods to determine the spatiotemporal dynamics of ecological land in the Nantong riverine area from 1980 to 2020 and further discussed the potential driving factors. We found that (1) from 1980 to 2020, the major types of ecological land changed from cropland (82.08%), water (17.19%), and grassland (0.69%) to cropland (70.11%), water (26.98%), and forestland (2.25%), and the ecological land area decreased by 4091.36 km^2 during the same period with a significantly increased dynamic degree of land use. (2) Spatial heterogeneity existed in the distribution and variation of ecological land. Water was the dominant ecological land use in the Yangtze River levee's inner area, with transitions to cropland and impervious surfaces as the primary conversion types; cropland was the primary land use in the levee's external area, with transitions from cropland and water to impervious surface as the primary conversion types. In addition, in cities with an early start and a high level of urbanization, most of the ecological land had been converted to impervious surfaces by urban development, whereas cities without those characteristics had retained more of their ecological land. (3) Ecological land change was influenced by a combination of natural and socio-economic factors, and there were enhanced-bi and enhanced-nonlinear interactions between them. (4) The dominant factors influencing ecological land changes during the three stages of urbanization (1980–2000, 2000–2010, and 2010–2020) were the distance to the Yangtze River, the population, and the GDP (Gross Domestic Product) of secondary industry, respectively. The role of environmental policies has gradually increased in recent years, which has played a positive role in ecological land use restoration. The findings of this study can assist policymakers in optimizing land use and restoring ecological space to conserve biodiversity.

Keywords: ecological environment; spatiotemporal distribution; driving force; land-use change; Geodetector; Nantong

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1. Introduction

Since the late 1970s, China's coastal regions have undergone rapid urbanization to varying degrees. According to the Seventh National Population Census, 63.89% of people live in urban areas [1]. The most predictable feature of urbanization is how it impacts land use zones, with urban expansion taking up a vast portion of ecological land and significantly contributing to ecological changes [2–5]. Ecological land is the primary source of regional ecosystem services and functions [6] and also serves to guarantee the essential ecological services in a complex urban ecosystem [7], which is critical for regional ecological conservation. Urban ecological land is key to sustainable land use and, therefore, has interested numerous scholars who have monitored and reported on the changes in vegetation coverage [8,9], built-up areas [10], wetlands [11], grasslands [12,13], and other related ecological indicators.

Changes in urban land use have resulted from a combination of multiple factors, of which the primary ones vary according to the city's geographic location, developmental stage and scale, and economic structure [14]. In Wuhan, the topography has dominated these changes while urban traffic, population, tertiary industry proportion, and the gross output value of agriculture have been the primary human factors [15]. In Beijing, the ecological space was formed in a green belt on the outskirts of the city as the population density and industrial structures expanded out from the city center [16]. In the Yellow River basin of Shandong Province, elevation, slope, and soil type have been the key factors affecting land-use change [17]. As research has broadened, the associated methodologies have become more diverse as well, with the most common methods being regression analysis models [18,19], geographically weighted regression [20], gray correlation analysis [21], and Geodetector [22].

Nantong City in Jiangsu Province is representative of China's rapidly urbanizing trends. It is located at the intersection of China's coastal economic belt and the Yangtze River Economic Belt. Economic development along the Yangtze River has resulted in negative consequences such as the unreasonable distribution and the inefficient utilization of a portion of the shoreline, especially the pollution caused by industrial production, which directly threatens the ecological environment of the Yangtze River [23], making it essential to improve shoreline protection and promote the construction of ecological security barriers. In December 2018, the state council of the People's Republic of China unveiled an action plan to protect and restore the Yangtze River, emphasizing strict shoreline protection and restoration and promoting urban ecological buffer zones on both sides of the Yangtze River mainstream to rehabilitate the shoreline's ecological functions. Influenced by the interaction of water and land, the shoreline is fragile, variable, and comprehensive [24,25], so it is not only the backbone of regional economic development and a critical component of the Yangtze River protection strategy's implementation but also an area with outstanding contradictions between development and protection [26,27]. The ecological protection of the Nantong section is crucial as the "last baton" in the race to protect this region. In recent years, environmental protection efforts have led to a significant improvement in the ecological environment along the river.

Therefore, a complete understanding of the spatiotemporal patterns of the ecological land in Nantong and its driving factors are essential for interpreting the interaction between human activities and the natural environment during urbanization and can optimize land use and provide a template for the effective implementation of similar conservation strategies in other regions.

This paper has the following structure: Section 2 provides a detailed spatial description of the study area; Section 3 describes the data and methods used. Section 4 presents the results obtained, including the changes in ecological land area and structure as well as the spatial distribution characteristics in the study area based on factor detection and intersection detection. Finally, in Section 5, we discuss the reasons for the spatially divergent characteristics of ecological land change in the study area and the dominant factors affecting ecological land change at different stages of urbanization.

2. Research Area

Nantong (120°11′51″–121°59′29″ E, 31°25′51″–32°42′47″ N) is on the southeast coast of Jiangsu Province and the northern flank of the Yangtze River estuary, where the river and the sea meet to form a riverine and marine sedimentary plain with gentle terrain and elevation between 0–115 m. In this study, the county-level administrative districts along the Yangtze River in Nantong were selected as the research area, including Rugao, Tongzhou, Chongchuan, Nantong Economic and Technological Development Area (NETDA), Haimen, and Qidong (Figure 1), with a total area of approximately 8975.17 km^2, a resident population of 597.22 million, and a regional gross domestic product (GDP) of CNY 765.92 billion (2020).

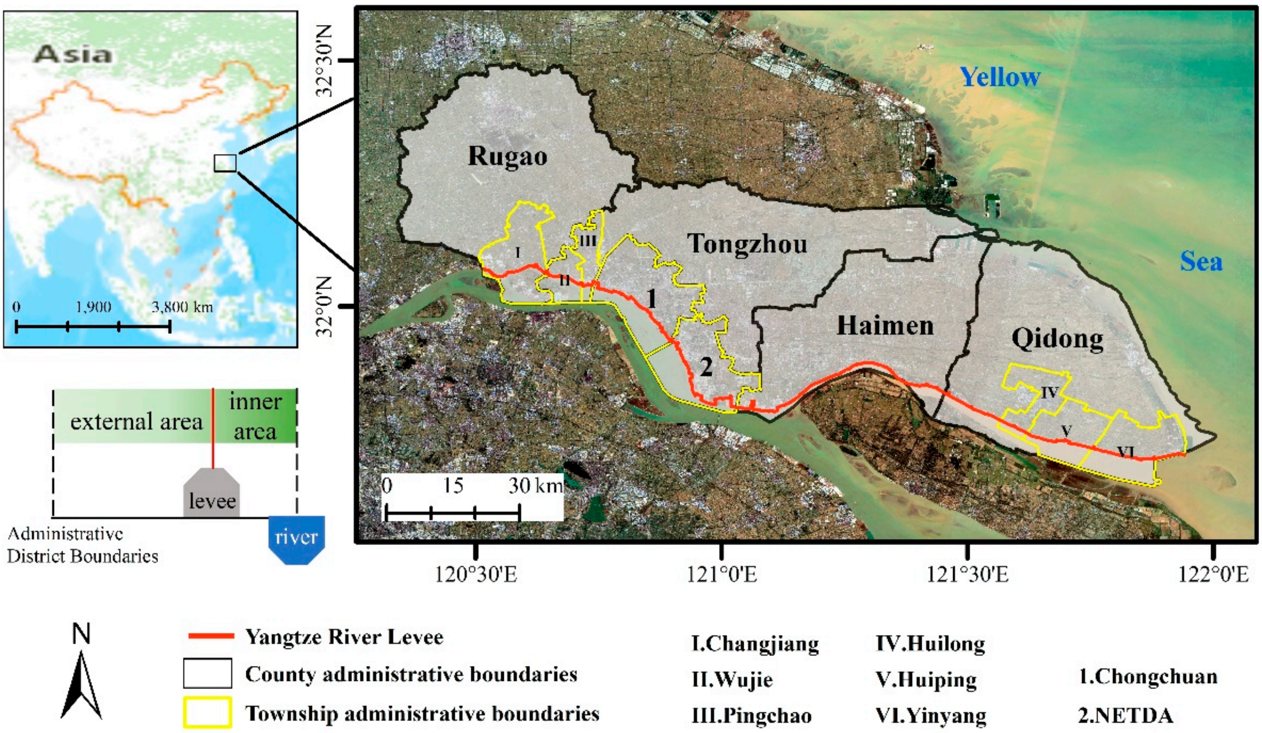

Figure 1. Location and scope of research area. White polygons and Arabic numerals indicate the boundaries and names of county administrative districts, while yellow polygons and Roman numerals correspond to township-level. The background image comes from Landsat 8 OLI with true-color composite (R: band 4, G: band 3, B: band 2).

The Yangtze River levee, spanning 227.60 km, was manually extracted for further spatial analysis using Google Earth remotely sensed images (Figure 1). The levee divided the research area into two parts. The inner region was the water–land interface zone, which is the primary ecological function area and is more sensitive to the environmental changes caused by human activities, with a total area of approximately 810.64 km^2, of which more than 60% is in Qidong, NETDA, and Chongchuan. In the remaining 40% of this inner section, we also selected some typical townships to obtain additional detailed information for analysis, and the total area, including the county- and township-level regions, was 657.83 km^2 and accounted for 81% of the total area of the internal region along the levee, which was reasonably representative. The external region, which extended northward from the levee to the administrative boundary of the county, is the primary production and living area with a higher population and traffic density than the internal region and has an area of approximately 8164.53 km^2. More than 70% of this region was in Rugao, Qidong, and Tongzhou. The levee-based spatial zoning was complemented with administrative districts to explain the characteristics of ecological land changes in the Nantong riverine area from an ecologically functional and structural perspective.

Since the administrative divisions of the riverine area have changed several times, all the names and the boundaries in this article were current as of the end of 2020.

3. Materials and Methods

3.1. Materials

3.1.1. Land Use Products

Four periods of land-use products were used in this study, including those around 1980 were provided by the Resource and Environment Science and Data Center (Available online:

https://www.resdc.cn/ (accessed on 10 September 2021)) at a spatial resolution of 1 km; those around 2000 and 2010 were provided by the National Earth System Science Data Center (Available online: http://nnu.geodata.cn:8008/ (accessed on 10 September 2021)) at a scale of 1:100,000 and a qualitative accuracy of 80–90% or better. The final dataset was released by ESRI in 2020 (https://livingatlas.arcgis.com/landcover/ (accessed on 10 September 2021)) and employs a novel machine-learning workflow to process a large number of sentinel-2 images at a spatial resolution of 10 m [28].

These land-use products are considered accurate and have frequently been used in related research [29–31]. However, they were derived from different data sources and processing algorithms that used different classification systems. To ensure consistency and comparability of the data across different time periods, this study unified the land-use types into the following categories based on the latest Chinese current land-use classifications (GB/T 21010-2017), which included impervious surface, grassland, cropland, forestland, bare land, and water, all of which were ecological land except impervious surface [32].

3.1.2. Statistical Yearbook

The China statistical yearbooks (county-level) and its township volumes published by the National Bureau of Statistics were used to obtain relevant social and economic indicators, respectively, with the China statistical yearbooks (county-level) covering the period 1983–2020 for county-level administrative areas (Table 1) and the township volumes covering the period 2014–2020 for township-level administrative areas.

Table 1. Information on indicators in the China Statistical Yearbook.

Type	Scope	Period	Socio-Economic Indicators
County-level	Rugao, Tongzhou, Chongchuan, NETDA, Haimen, Qidong	1983–2020	Year-end resident population, Urbanization level, Number of on-post employees at Year-end, GDP, Primary Industry as a percentage of GDP, Secondary Industry as a percentage of GDP, Industry as a percentage of GDP, Tertiary Industry as a percentage of GDP, Rural Labor Force, Public Budget Revenue, Public Budget Expenditure, Industrial Power Consumption.
Township Volumes	Changjiang, Wujie, Pingchao, Huilong, Huiping, Yinyang	2014–2020	Year-end resident population, Urban resident population, Urbanization Rate, Industrial GDP, Number of Enterprises, Employees in the enterprise, and Employees in secondary and tertiary industries.

3.2. Methods

3.2.1. Land Use Dynamic Degree (LUDD)

Land use dynamic degree is a score that reflects the rate of land change over a certain period and generally has two forms: single land-use dynamic degree (SLUDD) and comprehensive land-use dynamic degree (CLUDD). The former indicates the intensity of change in a specific land type within a certain spatial and temporal context, whereas the latter is the sum of the intensities of change for all land types in that space [33].

$$D_s = \frac{A_j - A_i}{A_i \times t} \times 100\% \tag{1}$$

D_s denotes the SLUDD, which contains the transfer of land between land categories [34], A_i and A_j denote the area (km^2) of a specific type of land at the initial and final time points, respectively. The variable t represents the duration of the study.

$$D_c = \frac{\sum_{k=1}^{n} \Delta LC_k}{\sum_{k=1}^{n} LC_k t} \times 100\% \tag{2}$$

D_c denotes the CLUDD, LC_k the area of land type k at the final time points (km^2), ΔLC_k is the absolute value of the sum of the area transferred from and to land type k during the study period (km^2), and t represents the time interval (years) [35].

3.2.2. Geodetector

To conduct a quantitative analysis of the influence of natural and socio-economic factors on ecological land change, we adopted the Geodetector method, which measures the spatially stratified heterogeneity (SSH) between ecological land change and all related factors and determines the degree to which each factor influenced the land change through the magnitude of similarity in spatial distribution patterns [36]. The advantage of the Geodetector method was its applicability to interpret relationships between various types of influences, including variables, quantities, and other numerical variables, and it has been widely used in research across many fields, including genetic biology [37], medical science [38–40], ecological and environmental sciences [41,42], and climate change [43,44].

The Geodetector method includes four different detectors (i.e., risk, factor, ecological, and interaction) [36]; factor and interaction detection at different scales were performed in this study.

$$q = 1 - \frac{SSW}{SST} \tag{3}$$

$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2 \tag{4}$$

$$SST = N\sigma^2 \tag{5}$$

where q defines the degree of coupling between two variables X and Y, and its value is strictly within [0, 1]; q = 1 indicates that X can explain 100% of the spatial divergence of Y while q = 0 means that Y is completely independent of X. SSW and SST stand for the summation of the within-strata variance and the pooled variance, respectively; N and σ^2 indicate the number of units and the variance of Y, respectively. The expression h = 1, 2, 3, . . . , L denotes the strata of variable X or Y.

Based on the q-value of each explanatory variable ($q(X_1)$, $q(X_2)$) and the q-value of two variables interacting ($q(X_1 \cap X_2)$), the interaction detection can be implemented with the determination formula shown in Table 2.

Table 2. Interaction relationship between explanatory variables (Xs).

Description	Interaction
$q(X_1 \cap X_2) < Min(q(X_1), q(X_2))$	Weaken, nonlinear
$Min(q(X_1), q(X_2)) < q(X_1 \cap X_2) < Max(q(X_1), q(X_2))$	Weaken, uni-
$Max(q(X_1), q(X_2)) < q(X_1 \cap X_2)$	Enhance, bi-
$q(X_1) + q(X_2) = q(X_1 \cap X_2)$	Independent
$q(X_1) + q(X_2) < q(X_1 \cap X_2)$	Enhance, nonlinear

In this study, the land-use change matrix was Y, and the explanatory variables (Xs) are shown in Table 3, where X1 represented the natural factor including the distance to the Yangtze River, and the others were socio-economic factors, all of which were sourced from statistical yearbooks. At the county scale, X2, X3, X4, and X10 were social factors; X5, X6, X7, X8, X9, and X13 were economic factors; and X11 and X12 were policy factors. On the township scale, X2, X3, and X4 were social factors while X5, X6, X7, and X8 were economic factors.

Table 3. Explanatory Variables (Xs) at the county and township scales.

County-Administrative Districts		Township-Administrative Districts	
Explanatory Variables	**Indicators**	**Explanatory Variables**	**Indicators**
X1	Distance to Yangtze River	X1	Distance to Yangtze River
X2	Year-end resident population	X2	Year-end resident population
X3	Urbanization level	X3	Urban resident population
X4	Number of on-post employees at Year-end	X4	Urbanization Rate
X5	GDP	X5	Industrial GDP
X6	Primary Industry as a percentage of GDP	X6	Number of Enterprises
X7	Secondary Industry as a percentage of GDP	X7	Employees in the enterprise
X8	Industry as a percentage of GDP	X8	Employees in secondary and tertiary industries
X9	Tertiary Industry as a percentage of GDP		
X10	Rural Labor Force		
X11	Public Budget Revenue		
X12	Public Budget Expenditure		
X13	Industrial Power Consumption		

4. Results and Interpretation

4.1. Ecological Land Shrinking in the Riverine Area of Nantong during 1980–2020

A comparison of land use products from different periods revealed a decline in the area of ecological land along the river, which was 8516.53 km^2, 8390.67 km^2, 7904 km^2, and 4425.17 km^2 in 1980, 2000, 2010, and 2020, respectively, accounting for 94.88%, 93.48%, 88.06%, and 49.31% of the total riverine area, respectively. A total of 4091.36 km^2 was reduced from 1980 to 2020 (Table 4), with 98% occurring outside the levee and the remainder accounting for 9.62% of the total area inside the levee.

Table 4. Structure and change of land use types in the riverine area of Nantong.

Land Use Type	1980		2000		2010		2020	
	Area/km^2	**Proportion**	**Area/km^2**	**Proportion**	**Area/km^2**	**Proportion**	**Area/km^2**	**Proportion**
Impervious surface	458.66	5.11	584.51	6.51	1071.08	11.93	4550.00	50.709
Grassland	58.76	0.65	65.81	0.73	38.75	0.43	19.53	0.221
Cropland	6989.94	77.88	6930.54	77.22	6514.50	72.58	3102.34	34.57
Forestland	3.61	0.04	3.89	0.04	3.02	0.03	99.75	1.11
Bareland					1.67	0.02	9.50	0.11
Water	1464.22	16.31	1390.43	15.49	1346.15	15.00	1194.05	13.30
Ecological land	8516.53	94.88	8390.67	93.48	7904.09	88.06	4425.17	49.31

4.2. Structure and Dynamic of Ecological Land

Before 2010, the ecological land structure of the entire riverine area was cropland, water, grassland, forestland, and bare land, in descending order. By 2020, forestland had overtaken grassland as the third-ranked ecological land type. In contrast to the subtle structure changes, the structural differences between the two sides of the Yangtze River levee were more noticeable (Figure 2). In the inner region, water had an absolute area advantage, accounting for 85.73% of the ecological land area on a multi-year average, followed by cropland (11.13%) and grassland (2.59%), while in the external region, the primary ecological land type was cropland (87.72%), followed by water (11.21%) and forestland (0.62%).

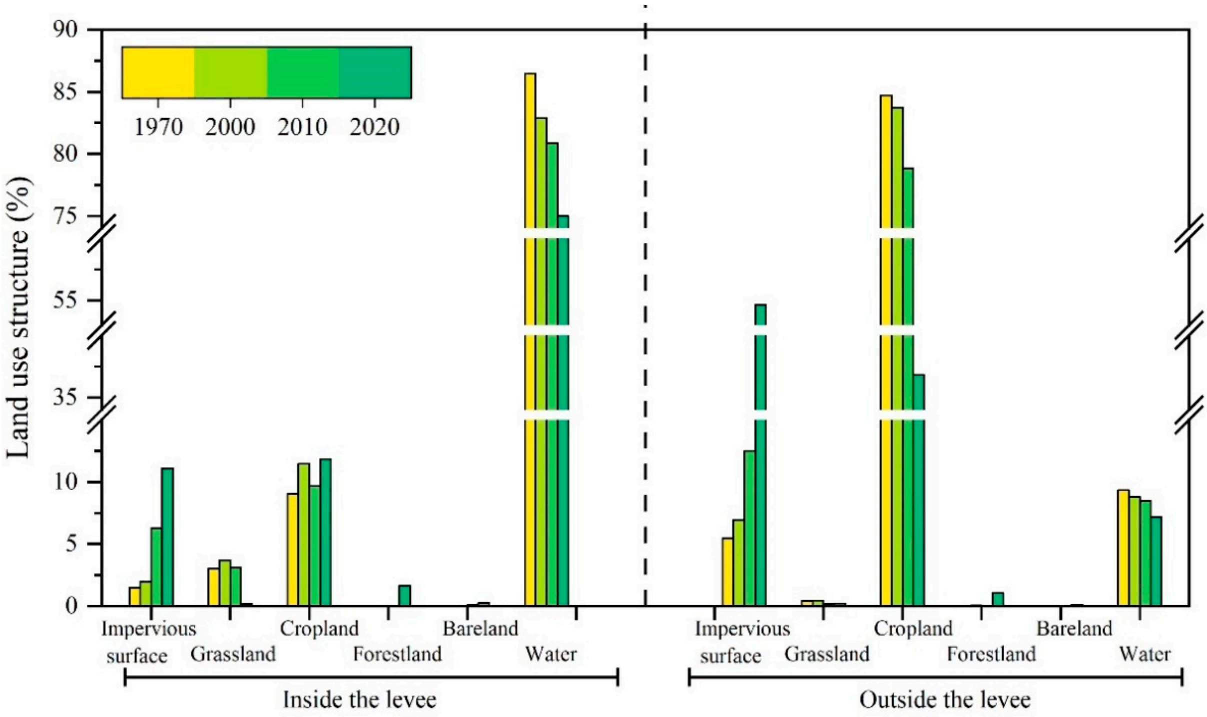

Figure 2. Histogram of land use structure on both sides of the Yangtze River Levee in Nantong (1980–2020).

Table 5 shows that (1) the absolute value of CULDD had increased, indicating that land change was accelerating in both regions of the Yangtze River levee. However, the CULDD in the inner area was greater than that of the external area until 2000, and then it reverted, and the CULDD of the external area was more than double that of the inner area after 2010, indicating that the focus on land-use change had shifted between the two sides of the levee from 1980 to 2020. (2) In terms of single land-use dynamic degree (SLUDD), water had a negative and increasing absolute value, indicating its accelerated shrinkage. Prior to 2010, the absolute value of the SLUDD of impervious surfaces was greater than that of all ecological lands, indicating that non-ecological land dominated the land-use change. However, after 2010, ecological land change became dominant, especially for forestland and bare land. The former was the most dynamic type of ecological land in the inner region, and the latter was in the external region. Cropland and grassland exhibited more complex dynamic changes as they had both decreased across the riverine area but had a marked difference on both sides of the levee: in the inner area, cropland had increased in recent years while grassland had accelerated its reduction, whereas the reverse was true for the external region.

Table 5. Land use dynamic degree on both sides of Yangtze River levee in Nantong (1980–2020).

Land Use Type	Whole Riverine Area			External Area			Inner Area		
	P1 *	P2	P3	P1	P2	P3	P1	P2	P3
impervious surface	1.37	8.32	32.48	1.37	7.94	33.72	1.55	22.12	7.62
grassland	0.60	−4.11	−4.96	0.2	−6.2	3.25	1.16	−1.62	−9.39
cropland	−0.04	−0.60	−5.24	−0.06	−0.59	−5.33	1.34	−1.57	2.24
forestland	0.40	−2.25	320.57	0.4	−2.27	2.77			13,707.38
bareland			46.78			61.45			21.61
water	−0.25	−0.32	−1.13	−0.29	−0.39	−1.52	−0.21	−0.24	−0.73
CLUDD	0.57	0.58	4.66	0.56	0.29	2.46	0.71	0.28	1.03

* P is short for Period, P1(1980–2000), P2(2000–2010), P3(2010–2020).

4.3. Spatial Patterns and Transformation Matrix of Ecological Land

Between 1980 and 2020, land use in the Nantong riverine area changed dramatically. The expansion of impervious surfaces had reduced the extent of ecological land as well as the fragmentation of its spatial pattern, especially for cropland (Figure 3).

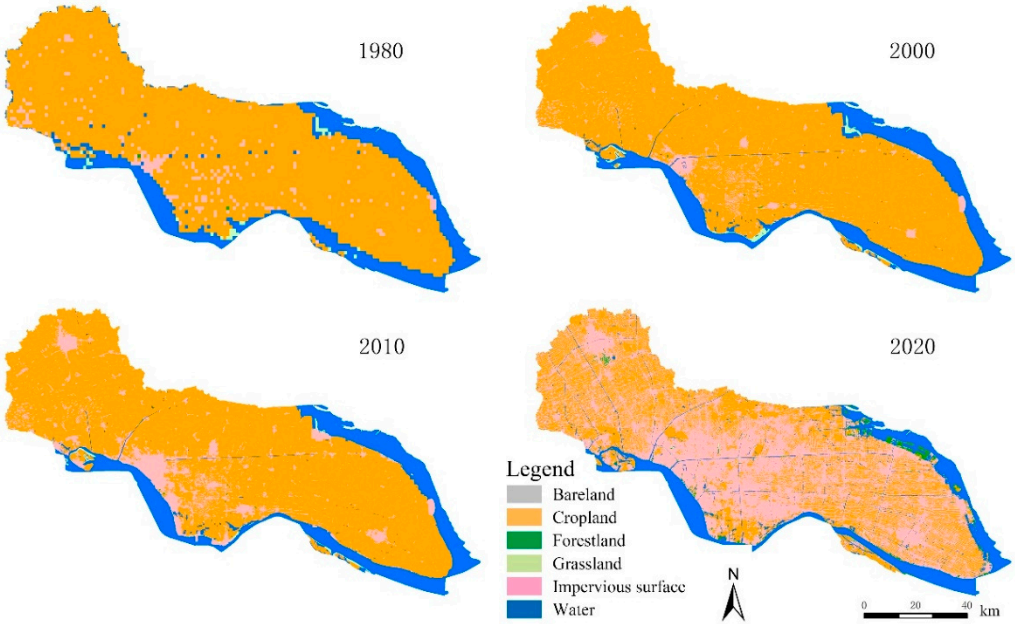

Figure 3. Land use maps in riverine area of Nantong during 1980–2020.

In 1980, most of the land along the river had been cropland surrounded by water, with some grassland distributed along the Yangtze River, some impervious surfaces in a dotted pattern in Chongchuan, and the remainder of the ecological land largely invisible. By 2000, the expansion of impervious surfaces had formed a clear polygon with more grassland along the Yangtze River due to artificial engineering. The expansion of impervious surfaces continued until 2020, forming a broad contiguous distribution and occupying a large area in the central region, while some forestlands were formed along the northeastern coastline.

The confusion matrix, also known as the Markov matrix, is a general technique for analyzing the characteristics of transfer between different land-use types over a period and is easy to implement using ArcGIS 10.7.

According to Tables 6–8, (1) the total land-conversion areas in the riverine regions during the three studied periods (1980–2000, 2000–2010, 2010–2020) were 1024 km^2, 524 km^2, and 4184 km^2, respectively, among which the conversion between ecological land and non-ecological land (impervious surfaces) accounted for 69.92%, 95.01%, and 91.30%, respectively. Cropland and water continued to be the primary sources of new impervious surfaces, with increasing contributions year over year. (2) In the external region, the conversion from ecological land to non-ecological land was the main trend and accounted for a greater proportion than the riverine area; cropland had the largest decrease among ecological lands. (3) In the inner region, the land conversion process was more complex: from 1980 to 2000, the conversion within the ecological lands had been more frequent (accounting for 86%), mainly between water, grassland, and cropland; from 2000 to 2010, the conversion between ecological land and non-ecological land had been dominant (78.86%), primarily as the conversion of cropland and water to impervious surfaces; during 2010–2020, the conversion within ecological lands had been dominant (53.74%), followed by the conversion between ecological land and non-ecological land (46.26%), with the former mainly from the conversion of water to cropland and forestland and the latter from the conversion of cropland and water to impervious surfaces.

Table 6. Matrix of land-use change during 1980–2000 (km^2).

1980	**2000**																	
	Whole Riverine Area						**External Area**						**Inner Area**					
	a	**b**	**c**	**d**	**e**	**f**	**a**	**b**	**c**	**d**	**e**	**f**	**a**	**b**	**c**	**d**	**e**	**f**
a *	164	0	282	1	11		158	0	279	1		8	5	0	3			3
b	0	25	11		22		0	20	7			8	0	5	5			14
c	400	8	6492	2	87		398	4	6444	2		68	3	4	48			18
d	0		3	0			0		3	0								
e																		
f	20	32	142			1270	12	12	105			634	8	20	36			636

* a, b, c, d, e, and f represent impervious surface, grassland, cropland, forestland, bareland, and water, respectively.

Table 7. Matrix of land-use change during 2000–2010 (km^2).

2000	**2010**																	
	Whole Riverine Area						**External Area**						**Inner Area**					
	a	**b**	**c**	**d**	**e**	**f**	**a**	**b**	**c**	**d**	**e**	**f**	**a**	**b**	**c**	**d**	**e**	**f**
a *	579	0	6	0	0	0	563	0	6	0	0	0	16	0	0		0	0
b	20	38	7			1	17	14	5			0	3	25	1			1
c	425	0	6494	1	2	8	408	0	6422	1	1	6	17	0	72	0	1	2
d	2		0	2		0	2		0	2		0						
e	0	0	0	0	0	0												
f	46	0	8		0	1337	31	0	3		0	684	14	0	4		0	653

* a, b, c, d, e, and f represent impervious surface, grassland, cropland, forestland, bareland, and water, respectively.

Table 8. Matrix of land-use change during 2010–2020 (km^2).

2010	**2020**																	
	Whole Riverine Area						**External Area**						**Inner Area**					
	a	**b**	**c**	**d**	**e**	**f**	**a**	**b**	**c**	**d**	**e**	**f**	**a**	**b**	**c**	**d**	**e**	**f**
a *	901	5	115	8	1	41	869	5	111	7	0	28	32	0	4	1	1	13
b	11	0	18	3	0	6	7	0	3	2	0	2	5	0	15	1	0	4
c	3511	11	2857	21	1	114	3484	10	2822	19	1	100	27	0	35	2	0	14
d	2	0	0	1		0	2	0	0	1		0	0		0	0		0
e	1	0	0	0	0	0	1		0	0	0		0	0	0	0		0
f	125	4	111	66	8	1032	98	3	69	58	7	456	27	1	42	8	1	577

* a, b, c, d, e, and f represent impervious surface, grassland, cropland, forestland, bareland, and water, respectively.

4.4. Analysis of Drivers of Ecological Land Change

According to the single-factor detection results, for the county administrative districts, the explanatory variable with the greatest explanatory power for land-use change from 1980 to 2000 was X1, and it was significantly higher than all other factors (Figure 4a, yellow bar), indicating that the natural environment had the greatest influence on land-use change.

From 2000 to 2010, the explanatory variables in descending order of q-values were X2, X4, X9, X7, X10, X5, X3, X8, X13, X6, X1, X11, and X12, with population-related indicators (X2 and X4) and GDP-related indicators (X7 and X5) as the main factors affecting land change. This indicated that the increase in the residential population increased the demand for land and led to changes in land-use types.

From 2010 to 2020, the explanatory variables in descending order of q-values were X7, X10, X5, X8, X13, X6, X12, X3, X2, X4, X9, X11, and X1. GDP-related indicators were the main factors influencing these land-use changes, especially the industry-related GDP (X7) and electricity consumption (X13), followed by population-related indicators (X2 and X4). X1 had the weakest influence on land changes, indicating that the demand for land as a result of the increasing population size had stabilized during this period; however, the demand for land for industrial production was the main cause of changes in ecological land use.

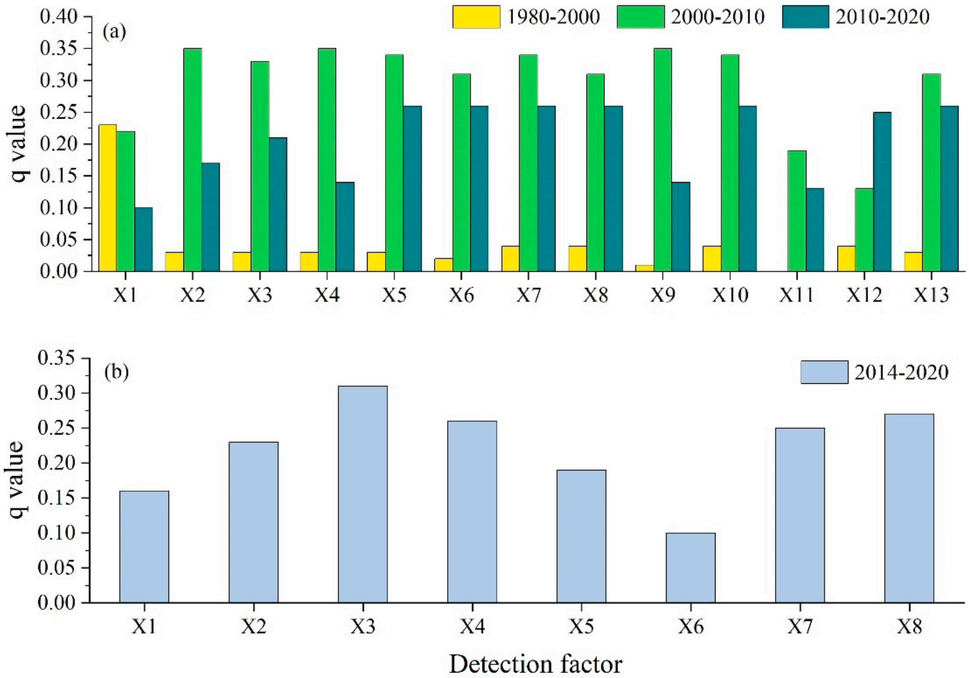

Figure 4. q-values of each explanatory variable at the scale of (**a**) city and (**b**) township in the riverine area of Nantong.

In the township-level administrative regions, the explanatory variables in descending order of q-values were X3, X8, X4, X7, X2, X5, X1, and X6 (Figure 4b), with population-related indicators overtaking the number of enterprises and output value indicators as the main factors influencing land-use changes in the townships along the river.

The results of the interaction detection showed that interactions existed among all explanatory variables, both at the city or township level and for different developmental periods (Figure 5), including both bi- and nonlinear enhanced. The bi-enhanced performed well for any pair of socio-economic factors, which meant the influence of any two-factor interactions was greater than that of any single factor. The distance to the Yangtze River (X1) and all other remaining factors were nonlinear enhanced, that is, the combination of any one socio-economic factor and the distance to the Yangtze River enhanced the original interpretation of the land-use changes but not more than the sum of the two alone, and these characteristics were verified at different stages of urbanization, including up to the present.

In 1980–2000, the distance to the Yangtze River (X1) and the number of on-post employees at year-end (X4) and tertiary industry as a percentage of GDP (X9) had the greatest explanatory power on land change when they acted together; in 2010–2020, it was the combination of any of the socio-economic factors with X1 that had a strong and equal effect on land change. It showed that even though the natural environment was no longer a directly dominant factor, it still acted indirectly on land-use changes through its influence on socio-economic activities. For example, in the townships, the two factors X1 and urban resident population (X3) had the greatest explanatory power for land change when acting together.

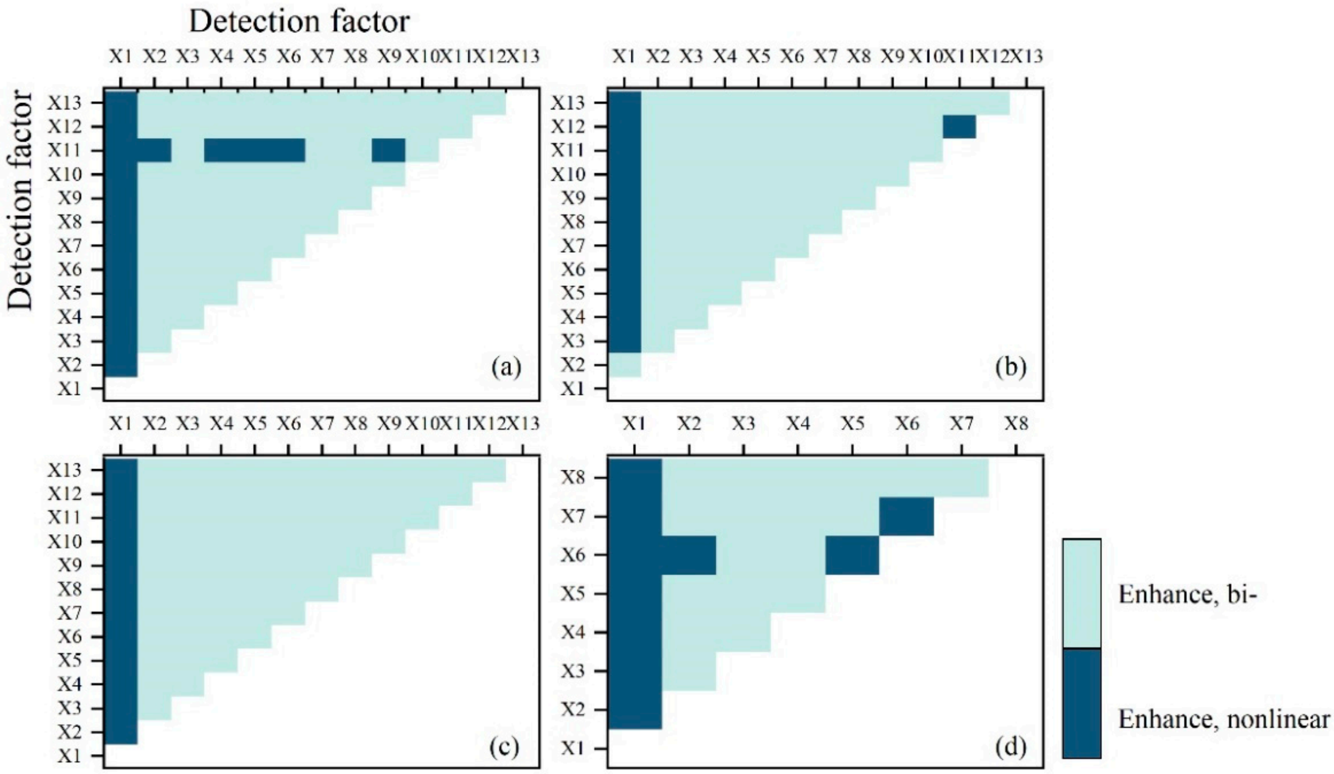

Figure 5. Heatmap of the interaction detection result, city-level in (**a**) 1980–2000, (**b**) 2000–2010, (**c**) 2010–2020, and township-level in (**d**) 2014–2020.

5. Discussion

5.1. Spatial Heterogeneity of Ecological Land Change

Based on the results, the area of ecological land had decreased at an accelerated rate during urbanization and its spatial distribution was relatively complex, with significant variability among different administrative regions. Furthermore, the experimental design of this study also yielded the expected results: the percentage and the dynamic features of ecological land varied on both sides of the Yangtze River levee.

Nantong was developed on an alluvial plain; the highly dense water system provided freshwater resources for agricultural production and formed a natural transportation network, so the ecological land at the confluence of the rivers was significantly reduced at the beginning of urbanization, especially as the built-up area expanded to occupy a large amount of cropland [45]. This was the main reason for the spatial differences in ecological land use between the two sides of the levee during the period 1980–2000. As the urban transportation network was extended further, the vast area outside the levee provided sufficient space for urban development, and more ecological land was occupied for urban production and living, so there was little difference in the change in ecological land on both sides of the levee between 2000 and 2010. As the urban development gradually shifted to the outer side of the levee, the production, living, and ecological spaces formed by urban planning led to the preservation and restoration of some ecological land (e.g., woodland and water) in the inner region of the levee. These caused the largest historical differences in ecological land changes on both sides of the levees during 2010–2020.

Among the several administrative districts in the riverine area, the variability of social attributes transcended geospatial correlations. For areas such as Chongchuan and NETDA, where urbanization started early and reached a high level, a large amount of land was required to support the population, so the ecological land was developed and utilized early. Rugao and Haimen, which had a later start for their urban development, had lower levels of urbanization and smaller cities [46], which preserved more of their agricultural production and ecological functions; therefore, a large amount of ecological land was preserved.

5.2. Impact of Natural and Socio-Economic Factors on Ecological Land Change

The results of the Geodetector method revealed that there were different dominant factors influencing the changes in ecological land at different stages of urbanization, and there were interactive enhancements among them, which was in agreement with previous studies [47,48]. According to past studies carried out in Nantong, transportation, population, industrial structure, urbanization level, and economic development level were once the main drivers of land-use change in Nantong [49,50], but it was not sufficient to answer the question of the drivers of ecological land-use change in the riverine areas of Nantong.

The Yangtze River has been a natural factor influencing the urbanization of Nantong as well as many other cities along the river [44]. The land has frequently changed along the riversides, and a large area of water provides opportunities for urban expansion, such as remodeling the riverside to form new land and ports and further expanding the economic radiation range by building bridges across the Yangtze River. This was also confirmed in Section 4.4, where the distance to Yangtze River was the absolute dominant factor influencing land-use changes during the early stages of urbanization and formed a non-linear enhanced effect with other factors during all three periods. As opposed to other cities along the Yangtze River, Nantong has a particular location advantage as the integrated gateway city to the northern wing of the Shanghai metropolitan region, which has directed Nantong's urban development towards the larger city and thus influencing the spatial patterns of its land use, including the spatial distribution of the industrial structure.

If natural factors are the basis of ecological land use, then socio-economic factors are the reflection of human activities, as the latter have impacted the natural environment and intensified ecological land-use changes, especially urbanization, which has been the main cause of the decline in cropland [51].

According to the q-value of each explanatory variable, the explanatory power of socio-economic factors began to increase in 2000 in the form of population-related factors and followed by GDP-related indicators. However, after 2010, the reverse was true, especially due to industry-related GDP (X7) and electricity consumption (X13), which had the strongest explanatory power. This was in line with a series of measures taken by the Nantong government: in 1995, the riverine zone had been planned as a priority zone for industrial land use, and by 2004, urban master planning had reemphasized the use of the Yangtze River levee and accelerated the urbanization process. In 2009, the establishment of Tongzhou prompted the outward migration of the population from Chongchuan and NETDA [21], and around 2010, the implementation of the "Yangtze River–Yellow Sea Linkage" policy in Jiangsu Province further expanded the development of industrial parks and the construction of ports along the river, resulting in significant land-use changes in the coastal areas [20]. Another noteworthy detail was that the X12 factor increased rapidly after 2010 (i.e., the explanatory power of government financial expenditure on land change had risen), which may have been related to an ecological civilization construction initiative in Nantong. In 2016, Nantong proposed to build an "urban living room" along the river, and in 2017, the ecological restoration and protection projects began to be implemented, heavy polluting enterprises were repaired, ports were relocated, and largescale afforestation was conducted to improve the environmental carrying capacity. These policies and related initiatives were also associated with the increase in the forestland along the Yangtze River in Nantong in the past ten years, instead of the typical decrease that occurs during similar periods of rapid economic development.

6. Conclusions

(1) The ecological land area along the river decreased by 4091.36 km^2 from 1980 to 2020, with 98% of change occurring in the outer region of the Yangtze River levee (i.e., the Nantong section)

(2) From 1980 to 2020, the main ecological land types in riverine areas were cropland and water, and forestland overtook grassland as the third-ranked ecological land type in 2020. The main ecological land type in the inner and outer regions of the levee were water and cropland, and they were also the ecological lands with the largest land-use dynamic degree in their respective areas. Until 2000, the outer region of the levee surpassed the inner region as the area with the highest degree of land change.
(3) The distribution pattern of water and land as well as the level of urban development were the driving factors behind the spatial heterogeneity of the ecological land distribution in the riverine areas.
(4) Land-use changes in the riverine area were influenced by both natural and socio-economic factors, but with the urbanization process, socio-economic factors gradually overtook natural factors as the main drivers of land-use change, which included the distance to the Yangtze River, the population, and the industrial GDP.

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