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Ecological Risk Assessment and Impact Factor Analysis of Ecological Spatial Patterns in Coastal Counties: Taking Dalian Pulandian District as an Example

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Abstract: A scientific foundation for the sustainable development of ecosystems and the improvement of the ecological spatial security pattern in the area is provided by carrying out a scientific assessment of ecological risk levels in coastal counties. An ecological risk assessment model was established in Pulandian district, Dalian, based on four periods of land use data from 1990 to 2020 combined with the PSR model. The spatial and temporal evolution of ecological risk in Pulandian was analyzed on this basis, and an exploratory regression analysis and a geographically weighted regression model were then used to explore the driving role of natural and social factors on comprehensive ecological risk in coastal counties. The findings demonstrate that there is an obvious ecological landscape type of conversion, with the majority of arable land being converted to forest land in northcentral and southwest areas, reflecting an improvement in the ecological environment and air quality, and the majority of coastal beach land being converted to construction land among the volumes transferred out and in. The area of high risk increased by 73.17% during the course of 30 years, with the majority of it concentrated in the research areas southern Fengrong, Tiexi, and Taiping regions in 1990 before expanding to the northeast, southeast, and central regions. The status index and response index both show a decline followed by an increase in change, while the pressure index shows a rising tendency with socioeconomic progress. The comprehensive ecological risk in the study area is significantly influenced by the urbanization rate, the ratio of environmental protection investment to GDP, the ecosystem service index, and the ecological space–land use ratio, with the urbanization rate displaying more overt negative correlation-driving characteristics, the ratio of environmental protection investment to GDP displaying significant spatial division characteristics, and the ecological space–land use ratio being an important factor. The findings serve as a foundation for decisions on ecological risk avoidance, control, and construction in Pulandian.

Keywords: ecological risk; PSR model; ecological space; geographically weighted regression; coastal counties

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Citation: Qu, M.; Tian, Y.; Liu, B.; Xu, D. Ecological Risk Assessment and Impact Factor Analysis of Ecological Spatial Patterns in Coastal Counties: Taking Dalian Pulandian District as an Example. *Sustainability* **2023**, *15*, 11805. https://doi.org/10.3390/su151511805

Academic Editor: Hariklia D. Skilodimou

Received: 28 May 2023
Revised: 23 July 2023
Accepted: 29 July 2023
Published: 1 August 2023

1. Introduction

As urbanization progresses, a variety of ecological issues brought on by people's more frequent use of the environment exacerbate the already precarious ecological situation, endangering not only the ecosystem in the area but also humankind's ability to live sustainably. Landscape ecological risk refers to the detrimental effects of human behavior or natural disasters on a population or ecosystem, and it measures how negatively human activity and natural change have affected the local ecosystem [1–3]. Ecological risk assessment, a crucial step in regional environmental restoration and ecological construction, is the assessment of the potential for harm to ecosystem structure and function brought on by human or natural factors. Different scholars have chosen pertinent indicators, models, and methods for different regions to carry out the ecological evaluation of the landscape in different regions, and they have formed a certain framework for ecological risk assessment research [4,5]. Domestic scholars have paid much attention to the discussion of ecological risk assessment theory and methods [4–6]. Some academics have investigated theoretical approaches that assess ecological risks using the water environment, ecology, and soil environment in the area [7,8], and some have measured water quality and soil pollution levels in coastal wetlands [9,10], but the majority of judgment indicators and approaches are still comparatively simple. Diverse stress factors, such as biological, physical, and chemical factors, have been combined with the development of ecological risk assessment [10–12], but the method indicators do not take into account socioeconomic and human activities, making it impossible to reflect the spatial and temporal changes in the ecological environment relative to the development of human society. Ecological risk assessment can be carried out more scientifically thanks to the development of 3S technology; domestic researchers employ the landscape pattern index, the element–landscape–society conceptual model, and other tools [13–16]. In order to undertake a risk assessment, some researchers additionally determine the hazard and vulnerability of the local ecological environment [17,18], concentrating more on the analysis of the local ecological condition and risk sources than on the feedback and reaction of ecological hazards relative to the outside world. By evaluating the causal relationships in the ecosystem and balancing stress, state, and reaction levels, the PSR model may offer a thorough and scientific view of regional ecological risk assessment. The model has been extensively used in ecological risk assessment studies for geographical units, like plateaus [19], lake areas [20], and watersheds [20], as well as for provincial [21] and municipal [22] scales above the county scale. However, ecological risk assessment studies for coastal county scales with fragile ecosystems and complex geographical environments are generally weak.

In order to examine the ecological spatial pattern of coastal areas, research on ecological space and ecological risk is mostly supported by GIS and remote sensing [23]. This research moves from ecosystem evaluation to ecological spatial patterns based on the spatial distribution of ecological risk levels, assessing their ecological risk intensity and disclosing the spatial and temporal variation characteristics of ecological hazards. Ecological space is the most significant ecosystem in coastal counties, and this study conducts pertinent research on the structure and landscape characteristics of its ecological space in order to reveal the significance of its evolutionary characteristics for ecological protection and green space planning in coastal counties. Dalian Pulandian district is located on the east side of the southcentral Liaodong Peninsula, bordering the Bohai Sea and the Yellow Sea, and is a representative typical coastal county with low mountains, hills, plains, salt flats, and mudflats. Pulandian district has been committed to the ecological and environmental protection of natural resources for many years, establishing a northern hilly mountain forest ecological protection zone, central low-hill plain ecological agriculture construction zone, southeastern low-hill coastal ecological coastal construction zone, and southwestern hilly bay ecological city construction zone. Four ecological environment zones are constructed according to the ecological sensitivity and ecosystem service function of different ecological zones. In this context, realizing the population, ecological, resource utilization, and economic aspects of reasonable coordination and the rational planning of ecological space, agricultural space, urban space, and orderly development is an important issue Pulandian district faces. In order to achieve this, this paper analyzes the spatial and temporal evolution characteristics of landscape types over the past 30 years, combines the landscape index analysis method and PSR model to construct the ecological risk index system, and investigates the coupling relationship between ecological spatial patterns and landscape ecology. Dalian Pulandian district, a coastal county, is chosen as the study area, and the streets (townships) serve as the basic unit of study. Coastal counties' spatial optimization can serve as a guide.

2. Materials and Methods

2.1. Study Area

With a geography that features low mountains, hills, plains, a sea, and a coastline of 187 km [24] (Figure 1), Pulandian district is situated in the southcentral east side of the Liaodong Peninsula. Its coordinates are 121°50′33″ E to 122°36′15″ E and 39°18′25″ N to 39°59′00″ N. Pulandian district has a 9.7 °C annual average temperature, four distinct seasons, and a temperate monsoon climate [24]. According to the China Marine Statistical Yearbook (2017), there are 23 coastal districts and counties (county-level cities) in Liaoning province, with Dalian accounting for 45.45% of the total, and four districts bordering both the Yellow Sea and the Bohai Sea, such as Pulandian district, Jinpu New district, Ganjingzi district, and Lushunkou district. Among the 22 districts and counties ranked from the smallest to the largest, Pulandian district ranked 18th in total area and 14th in per capita land area. In terms of climate, the district's average temperature ranked 13th, which is not substantially different from the average temperature of coastal districts and counties in Liaoning. The total population ranked sixth to seventh, which is slightly higher than 13% of the average population in coastal districts and counties in Liaoning. The per capita GDP in 2020 ranked 14th, which is lower than the average per capita GDP in coastal districts and counties in Liaoning 19.6%. With a comprehensive Pikou port combining people, fishery, and cargo, Pulandian offers a distinctive human environment. Its southern part is dominated by aquaculture, which is one of the economically developed areas and highly developed towns in the Liaodong Peninsula. Its northern part is dominated by mountains, water, and forest economies, including the Biliu River reservoir scenic area, Anbo hot spring, and Laomao Mountain scenic area. The administrative limit of the town area, which includes 18 streets including Lejia, Tiexi, and Fengrong [24], divides the study's scope (Figure 2).

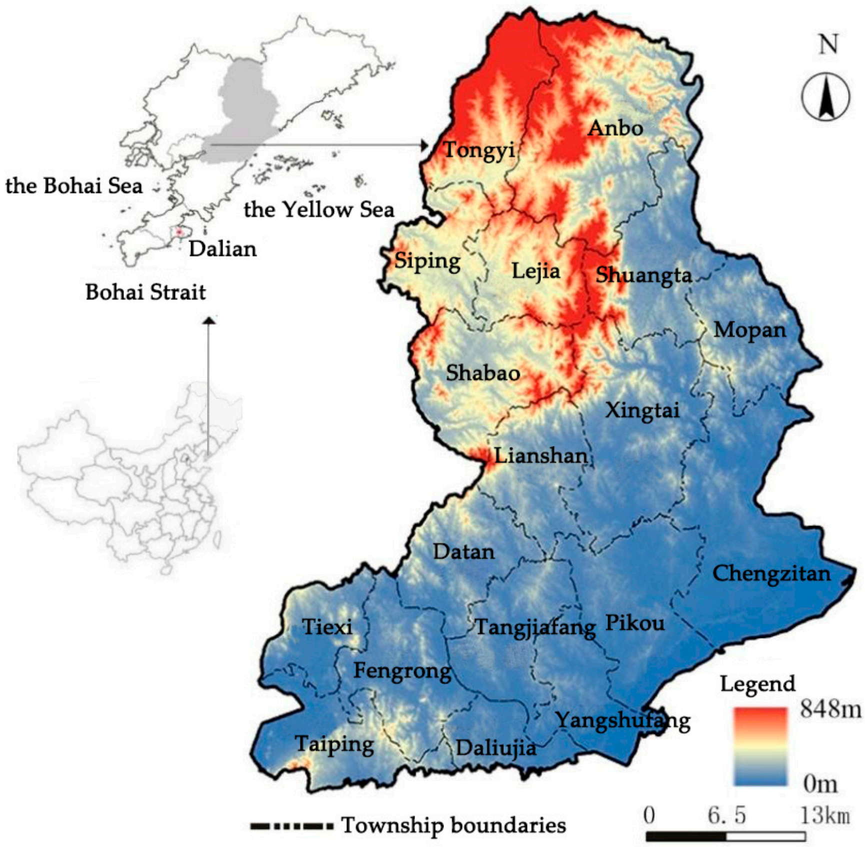

Figure 1. Orientation map.

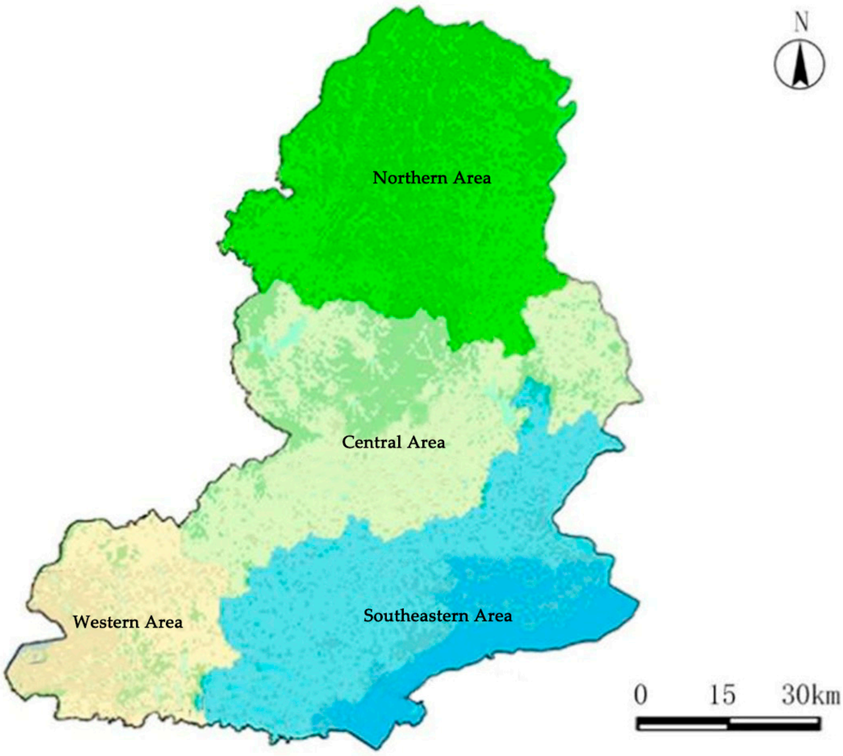

Figure 2. Map with the existing uses.

The dataset created by Yang and Huang [25] served as this study's data source for land use information. The land use data for 1990, 2000, 2010, and 2020 (spatial resolution 30 m), and their seven land types—forest land, grassland, watershed, coastal mudflats, construction land, arable land, and unused land—were classified into seven groups. Grassland, forest land, watershed, and coastal mudflat land were defined as ecological spaces based on national standards and related studies. Elevation data were obtained from the National Geographic Information Public Service Platform (https://www.tianditu.gov.cn, accessed on 19 April 2023), and the administrative division of Pulandian (1:1 million) was sourced from the Chinese Academy of Sciences Geospatial Data Cloud (https://www.casdc.cn/, accessed on 19 April 2023). The Pulandian Yearbook for 1990–2020 served as a source of economic and social indices. Field research was conducted in the study area to understand the landscape distribution and location of the study area.

2.2. Construction of Ecological Risk Index System of PSR Model

2.2.1. Classification of Evaluation Units

Evaluation results were quantified, and the data were more logically represented in space in order to examine the spatial and temporal evolution traits of the landscape ecological risk in Pulandian district. The study area was divided into 0.5 km $\times$ 0.5 km cells as evaluation units, and the comprehensive ecological risk index was calculated for each evaluation unit. The ecological risk index value of the center of the evaluation unit was used to obtain the spatial distribution of ecological risk values in the study area. This was carried out using Arc GIS software, the actual situation of the study area, and references to pertinent theoretical research results [13–22,26].

2.2.2. PSR Model and Evaluation Index Selection

The PSR model builds the PSR indicator system of responses by beginning with the cause and effect of landscape ecology [27]. It has three indicators: pressure, status, and response indicators. A total of 12 landscape ecological risk evaluation indicators were chosen for Pulandian District based on the pertinent literature [1,27] and combined with the unique characteristics of the study area. These indicators included 6 pressure indicators (population density, per capita GDP, urbanization rate, the proportion of gross output value of agriculture, forestry, animal husbandry, fishery, per capita forest area, and the proportion of construction land area), 3 state indicators (population density, and per capita forest area), and 6 pressure indicators.

The ecological service value is used by the ecosystem service index for evaluations [28,29]. Each land use type's ecological service value per unit area is calculated using the following criteria: forest land corresponds to forests, arable land corresponds to farms, garden land corresponds to grasslands, unused land corresponds to wasteland, water corresponds to rivers and lakes, and construction land is assigned a value of zero. Combining findings from earlier studies, the ecological service value of each land use type per unit area is estimated to be CNY 19,276 for forest land, CNY 6406.5 for grassland, CNY 40,676.4 for water, CNY 55,489 for coastal mudflats, CNY 6114.3 for arable land, and CNY 0 for construction land.

The landscape disturbance degree index, landscape loss degree index, and landscape fragility degree index were used to build the landscape ecological risk intensity evaluation model in accordance with prior studies and when paired with the features of the study area. Their compositions are as follows:

$$S_i = 0.6C_i + 0.3N_i + 0.1D_i \tag{1}$$

$$R_i = S_i \times F_i \tag{2}$$

$$ERI_i = \sum\nolimits_{i=1}^{N} \frac{A_{ki}}{A_k} R_i \tag{3}$$

where k in A_{ki} stands for the ecological risk unit; i stands for the area of the landscape component; S_i is the disturbance index; N_i is the landscape separation; C_i is the landscape fragmentation; D_i is the landscape dominance. Additionally, whereas ERI_i denotes the ecological risk index of the landscape in risk evaluation i, A_{ki} denotes the total area of the k-th risk unit.

The state of various elements that are both inside and outside of the ecosystem can be used to gauge its ecological resilience [30,31]. The state of various system components and the interactions between them can be used to gauge an ecosystem's ecological resilience. Each ecological component's relevant attributes can be reflected using the ecological resilience score. Citing the pertinent academic literature [29–33], the following equation was employed in this investigation within the context of the study area:

$$E_{CORES} = \left(-\sum\nolimits_{i=1}^{n} S_i log_2 S_i\right) \times \sum\nolimits_{i=1}^{n} S_i P_i \tag{4}$$

In the formula, i is the type of land use, S_i denotes the area of land type i as a proportion of all land use types, P_i denotes the resilience score of land type i, and E_{CORES} denotes the ecology of the region.

2.2.3. PSR Evaluation Weight Determination Method

The mean squared difference decision approach, which has great accuracy, and the more popular entropy weight method are both used in the construction of the PSR indicator system in this study. Each evaluation index is treated as a random variable in the mean squared difference decision technique, and each index's weight is determined using the mean squared difference of the processed attribute values. The mean squared deviation, which is the standard deviation of the random variable, must first be acquired and normalized, and the resulting value can be used as the weight coefficient for each indication. The steps in the formula are as follows:

$$E(J_I) = \frac{1}{M}\sum_{i=1}^{m} y_{ij} \tag{5}$$

$$\sigma(J_i) = \left[\sum_{j=1}^{n}\left(y_{ij} - E(J_i)\right)^2\right]^{0.5} \tag{6}$$

$$v_i = \sigma(J_i)/\sum_{i=1}^{n}\sigma(J_i) \tag{7}$$

The term "entropy weighting method" refers to the mathematical process of computing a composite indication based on the amount of information provided by each factor [34] and using the size of an indicator to calculate the weight. It was first used in the field of thermodynamics. The entropy weight method, which is an objective method of finding weights [1] when completing the calculation of the ecological safety index's assignment, eliminates problems that are associated with methods that artificially determine index weights, which are carried out by experts, scholars, etc. The following weighting formula is computed by using the entropy weighting approach in this paper:

$$X = \left(x_{ij}\right)_{m\times n}(i = 1,2,\ldots,m; j = 1,2,\ldots,n) \tag{8}$$

$$y_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \tag{9}$$

$$y_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}} \tag{10}$$

$$H_j = \frac{\sum_{i=1}^{n} Y_{ij} In Y_{ij}}{Inn} \tag{11}$$

$$w_j = \frac{1 - H_j}{\sum_{j=1}^{n}(1 - H_j)} \tag{12}$$

where x_{max} and x_{min} denote the maximum and minimum values under the j-th indicator of the i-th sample, respectively; m is the number of study samples; and n is the number of evaluation indicators for each sample, $Y_{ij} = y_{ij}/\sum_{i=1}^{m} y_{ij}(i = 1,2,\ldots,n)$.

2.2.4. Synthesis of Integrated Ecological Risk Evaluation Index

The assessment of landscape ecological risk involves a thorough review of numerous indicators [35–37]. The spectrum of different indicators is broad, and the value range is also very diverse. Since the scales of the indicators vary and the indicators do not agree with one another, there is little comparability and no way to assess it directly. The economic, social, and ecological effects of the research region are categorized and standardized in this study using 12 indicators. The classification is broken down into four levels: high ecological risk zones, higher ecological risk zones, medium ecological risk zones, and low ecological risk zones. To more accurately assess the ecological danger of Pulandian district, we intend to remove the inaccuracies that are brought on by unit inconsistencies between the data of each indicator.

2.3. Geographically Weighted Regression GWR Model

A spatial regression model called geographical weighted regression (GWR) illustrates how independent variable effects on explanatory variables can vary spatially [38]. This study uses the GWR module in the ArcGis platform to examine the link between ecological risk and its constituent parts based on the GWR model. The GWR model's formula is described as follows:

$$y_i = \beta_0(u_j, v_i)\sum_{i=1}^{p}\beta_i(u_j, v_j)x_{ij} + \varepsilon_j \tag{13}$$

where u_j, v_i denotes the observed geographic location coordinate of the observation point; y_i denotes the landscape index; i and j are the regression points for model calibration; $\beta_0(u_j, v_i)$ denotes the observation point i, space j intercept; and $\beta_i(u_j, v_j)$ is the independent variable. The local estimation coefficient of is x_{ij} (Figure 3).

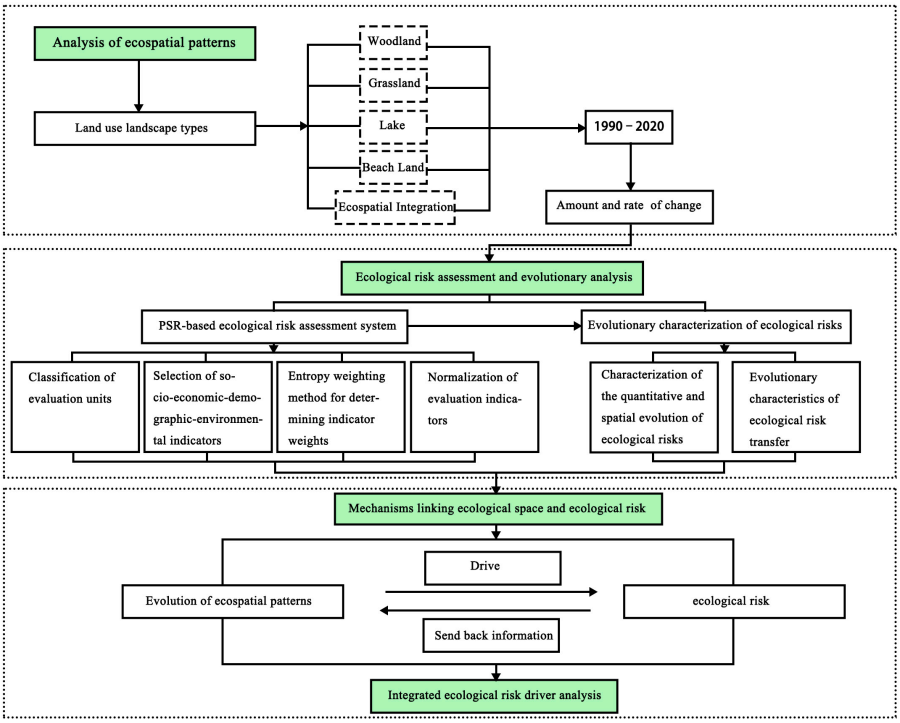

Figure 3. Flowchart diagram.

3. Results

3.1. Ecological Spatial Pattern Analysis

Pulandian district's land use structure underwent significant change between 1990 and 2020, with major variations in the alterations of the main landscape types (Figure 4). The three together account for almost 90% of the whole research area. In Pulandian district, arable, forest, and building lands are the dominant land use landscape types. The areas of Laomao Mountain scenic area, Jiguan Mountain scenic area in the northcentral part, and National Forest park in the southwest are primarily reflected as woodlands. The Biliu River reservoir, Daliang Ho reservoir, Biliu River, and Dasha River in Anpo are the main water distribution locations. The research area's coastal mudflats are primarily located in the southeast and southwest, particularly in Yang Shufang and Daliujia's western portions. The dominating landscape types in Pulandian district are agriculture and forestry production lands according to the land use landscape types.

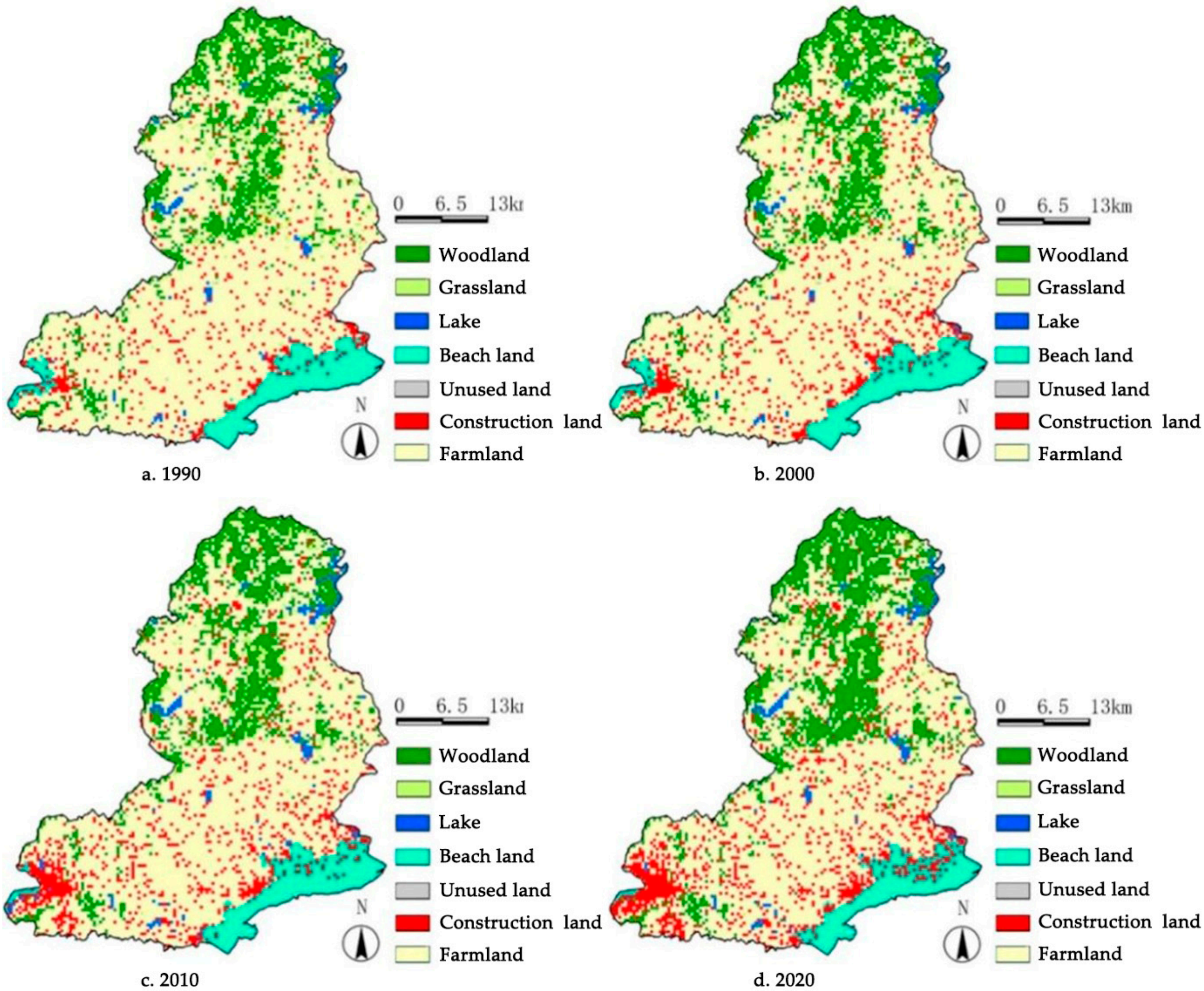

Figure 4. Changes in land use and landscape characteristics in the study area over four periods, 1990, 2000, 2010, and 2020 (0.5 km sample network).

The overall area of ecological space increased by 51.725 km^2 in 30 years, with an increase of 6.80% according to an analysis of the landscape types in the four periods shown in Table 1. In comparison to the decrease in grassland and coastal mudflats and the overall increase in water area, the increase in woodland is substantially larger. Woodland is the landscape type that experienced the greatest changes with respect to area, growing by 31.92% between 1990 and 2020, 8.57% between 1990 and 2000, and 1.19% between 2000 and 2010 Table 2, indicating that the region's economic development started around 2000 and had some effects on the ecological environment. This is related to the finding that as more land is developed to meet the needs of human material life, the type of land use landscape is increasingly disturbed by outside forces. The structure of land use in the study area is influenced at varying degrees by the economy, population growth, and social construction of the area.

Table 1. Two methods for calculating weights: entropy weights and mean square differences.

Guideline Layer	Indicator Layer	Entropy Method	Mean Square Error Method	Combined Weights	Positivity and Negativity
Pressure	Population density	0.0278	0.0800	0.0539	Negative
	GDP per capita	0.1015	0.0870	0.0943	Positive
	Urbanization rate	0.0693	0.1059	0.0876	Negative
	Total output value of agriculture, forestry, animal husbandry, and fishery as a percentage of agriculture, forestry, livestock and fisheries	0.0526	0.0773	0.0649	Positive
	Forest land area per capita	0.0237	0.0712	0.0475	Positive
	Percentage of construction land area	0.2317	0.0947	0.1632	Negative
Status	Ecosystem services index	0.2010	0.0931	0.1470	Positive
	Ecological resilience index	0.0628	0.0837	0.0732	Negative
	Landscape ecological risk intensity	0.0720	0.0912	0.0816	Positive
Response	Percentage of ecological space	0.0530	0.0676	0.0603	Positive
	Landscape diversity index	0.0245	0.0675	0.0460	Positive
	Environmental investment as a percentage of GDP	0.0802	0.0809	0.0806	Positive

Table 2. Analyses of changes with respect to Pulandian district's ecological area landscape types from 1990 to 2020.

Type	1990–2000		2000–2010		2010–2020		1990–2020	
	Amount of Change/km^2	Rate of Change/%	Amount of Change/km^2	Rate of Change/%	Amount of Change/km^2	Rate of Change/%	Amount of Change/km^2	Rate of Change/%
Woodland	35.901	8.57%	−5.418	−1.19%	103.283	22.97%	133.766	31.92%
Grassland	−26.885	−23.80%	−1.986	−2.31%	−34.675	−41.23%	−63.546	−56.25%
Waters	−3.528	−9.58%	17.824	53.54%	−6.183	−12.10%	8.114	22.04%
Coastal mudflats	2.883	1.51%	−14.553	−7.49%	−14.940	−8.31%	−26.610	−13.91%
Ecological space integration	8.371	1.10%	−4.132	−0.54%	47.486	6.21%	51.725	6.80%

3.2. Spatial and Temporal Evolutionary Characteristics of Ecological Risks

3.2.1. Comprehensive Ecological Risk Level Change and Spatial Distribution

The weights of the PSR model's indicators were determined in accordance with Equations (1)–(12) using the entropy weighting method and the mean square difference decision method. The findings are displayed in Table 3. The fraction of construction land area, the ecosystem service index, and the GDP per capita have the highest weights in the computation of weights based on the entropy weighting approach, indicating that there are greater regional disparities in the data for these measures. The weights of the urbanization rate, construction land area ratio, ecosystem service index, and landscape ecological risk intensity are relatively large according to the mean square difference method, which also shows that human activities and construction land have the most substantial effects on ecological risk. Population density, per capita woodland area, and the indicator of landscape diversity are assigned less weight in the overall weight. Therefore, reducing human activity's disruption of the ecological spatial system and controlling the chaotic and haphazard building on land are crucial to lowering ecological risks in coastal counties.

The ecological risk in the research region was assessed across four periods in accordance with the PSR model and Table 3, and the results are displayed in Figure 5, Figure 6 and Table 4. When compared to the pressure levels of 0.3201, 0.3214, 0.3291, and 0.3654 in 1990, 2000, 2010, and 2020, respectively, the ecological risk in Pulandian district showed a linear upward trend. The ecological risk in the area increased dramatically over the past 30 years, increasing by 0.0453 or 14.14%; the largest increase occurred between 2010 and 2020, increasing by 11.03%. The research area's high-risk areas considerably increased between 1990 and 2020, particularly in the southern parts, including Fengrong, Tiexi, and Taiping. During the 30-year period, the high-risk areas increased by 73.17%; they were first distributed in the southern portion of the research area in 1990 and then spread to the northeast, and by 2020, they had taken up the majority of the central, southeastern, and northern eastern sides. As urbanization advances, the central part of the study area gradually transitioned from a medium-risk to a higher-risk area, with the medium-risk area in the central region declining dramatically. The area with greater risks experienced the largest increase (32.33%) between 1990 and 2000. The high ecological risk area changed the most, with an increase of 8.76% between 2000 and 2010, whereas the higher-risk and low-risk zones all exhibit a tendency to increase. High-risk and higher-risk areas increased from 2010 to 2020, making up 11.43% and 26.11% of the total area. Overall, the high-risk and higher-risk areas in the study area displayed a clear increasing trend over the course of a 30-year period, while the low-risk areas displayed a trend that first decreased, increased, and then decreased, while the medium-risk areas displayed a continuously decreasing trend. This suggests that the study area's landscape ecological risk displayed an increasing trend.

Table 3. The research area's size and the percentage of ecological risk classes from 1990 to 2020.

Risk Level	1990		2000		2010		2020	
	Area/km^2	Proportion/%	Area/km^2	Proportion/%	Area/km^2	Proportion/%	Area/km^2	Proportion/%
High risk	287.35	10.74%	401.64	15.01%	436.81	16.33%	486.76	18.19%
Higher risk	461.86	17.26%	611.20	22.84%	634.20	23.70%	799.80	29.89%
Medium risk	1255.16	46.91%	1164.49	43.53%	1070.41	40.01%	972.79	36.36%
Low risk	671.05	25.08%	498.09	18.62%	534.00	19.96%	416.07	15.55%

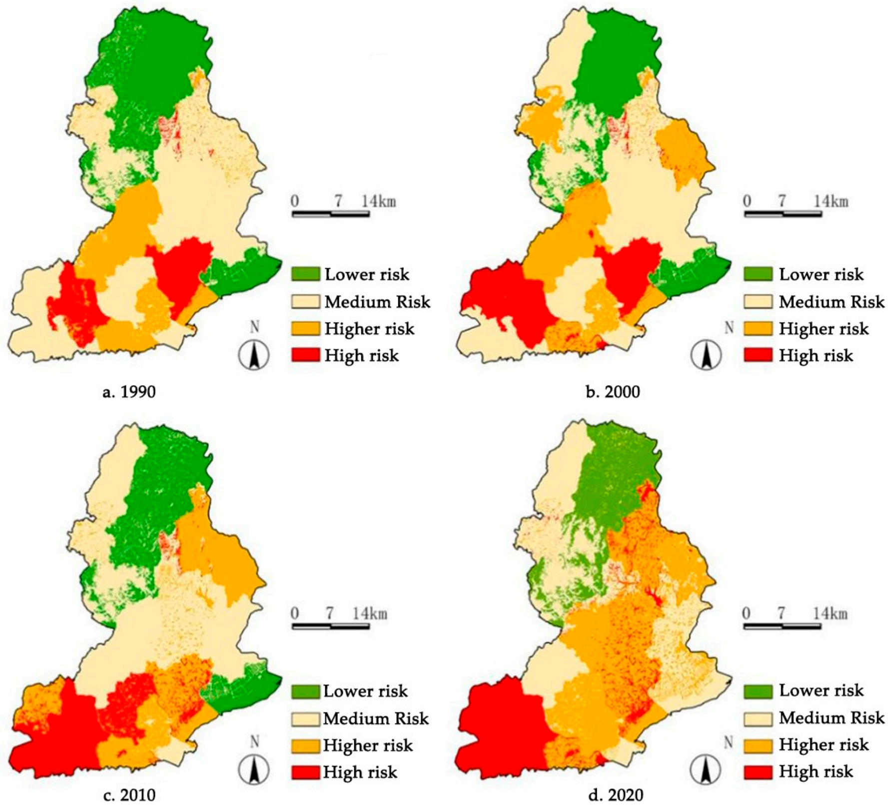

Figure 5. Spatial distribution of ecological risks in the study region for four periods 1990 to 2020.

Table 4. Comparison of GWR coefficients for the cumulative ecological risk as a result of several factors.

Driving Factors	Minimum Value	Maximum Value	Average Value	Standard Deviation
Urbanization rate	−0.032	−0.007	−0.018	0.007
Environmental investment as a percentage of GDP	−0.075	0.449	0.058	0.154
Ecosystem services index	0.128	0.446	0.247	0.096
Percentage of ecological space	0.281	0.396	0.325	0.036

3.2.2. Characteristics of Changes in the Integrated Ecological Risk Subsystem

With an increase of 19.61% over 30 years, the pressure change in ecological risks in the Pulandian district exhibits a linear increasing trend. The rate of pressure change was 3.05 times greater in 2010–2020 than it was in 1990–2000, showing that the main pressure variables affecting the area's ecological risk are rapid urbanization and economic development. Figure 6's analysis of the changes in each component of the pressure subsystem between 1990 and 2020 reveals that the northeast and southeast fall within the low-pressure category, the central region falls within the medium-pressure category, and the north and the south are in the high-pressure category. The rate of urbanization and the percentage of construction land area experienced the most substantial increases, with changes of 70.94% and 63.89%, respectively, with respect to the pressure indicator. The diverse requirements of transportation, traffic, and industry have resulted in a significant change in the type of land use in the context of the ongoing construction of infrastructure in Pulandian district. The distribution of ecological pressure is comparable to this. The area of forest land per person first decreased and then increased, which suggests that the study area pays increasing attention to the ecological environment, which is helpful for the ecological environment's improvement.

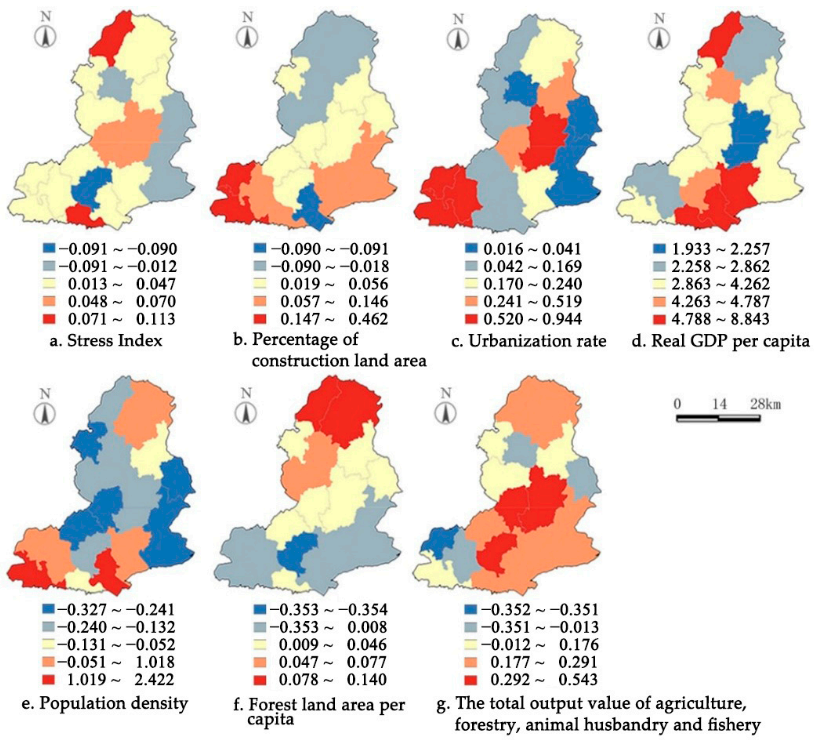

Figure 6. The research area's ecological stress indicators over time (1990 to 2020).

In Pulandian, the state index of ecological risk exhibits a tendency to first decrease and then increase (Figure 7); during a period of 30 years, the state value increased by 16.67%, and the state-level index increased more spatially in the south and center than in the north. The overall ecological risk intensity is a key state variable for the region and can accurately describe the regional ecological status. Indicating that the ecological risk intensity of the area is increasing as a result of the influence of human activities during the past 30 years, the landscape ecological risk intensity index from 1990 to 2020 showed a decreasing and then increasing trend, with an overall increase of 33.52%. Exhibiting a general increasing, decreasing, and then increasing trend and with 2010 as the turning point, the ecological service index can indicate the service capacity and breadth of the ecosystem. This trend suggests that the region realized the importance of the ecological environment when its economy developed in 2010, and the region started to focus on ecological restoration and protection. Similar to the situation with ecological services, ecological elasticity has a tendency to decrease and then increase, peaking in 2020. The cause of this is likewise related to the improvements in the ecological environment as people became conscious of the need to protect the environment. The study area gradually focused on ecological restoration and protection in the western part of the country, which has more construction land, and the central part of the country, which has more arable land, as ecological elasticity in these regions increased more than in other regions in terms of spatial distributions.

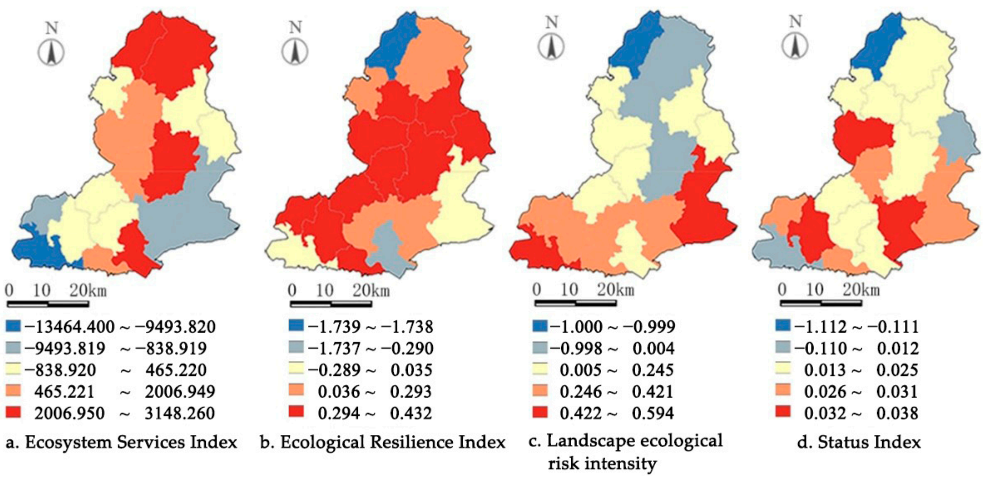

Figure 7. Changes in the research area's ecological status indicators between 1990 and 2020.

The Pulandian ecological risk response index (Figure 8) showed a tendency to first increase and then decrease, demonstrating a general improvement in the ability of ecosystems in the study area to mitigate ecological risks. The response index increased by 1.59% over 30 years. The proportion of ecological space in the response index exhibited a continuous decreasing trend, and the decline from 2000 to 2010 is 3.36 times greater than that from 2010 to 2020, indicating that ecological land was becoming increasingly scarce prior to 2010 due to economic growth and the expansion of urban land, while ecological land's significance was realized in 2010 as a result of increased environmental protection awareness and the support of relevant national policies. The landscape diversity index exhibits a pattern that initially decreased but was followed by a subsequent increase, with the latter tendency being more pronounced in the west and southeast areas. The ratio of investments in environmental protection to GDP shows a general intensified decreasing trend that then increased and then decreased, and its highest index was observed in 2010, which demonstrates that people began to pursue improving their living conditions as a result of the rapid economic development. The central and southern regions of the nation have higher spatial distributions in terms of investments in environmental protection; these regions also have higher rates of urbanization and GDP per capita growth, indicating a shift away from economic development toward an emphasis on ecological and environmental benefits.

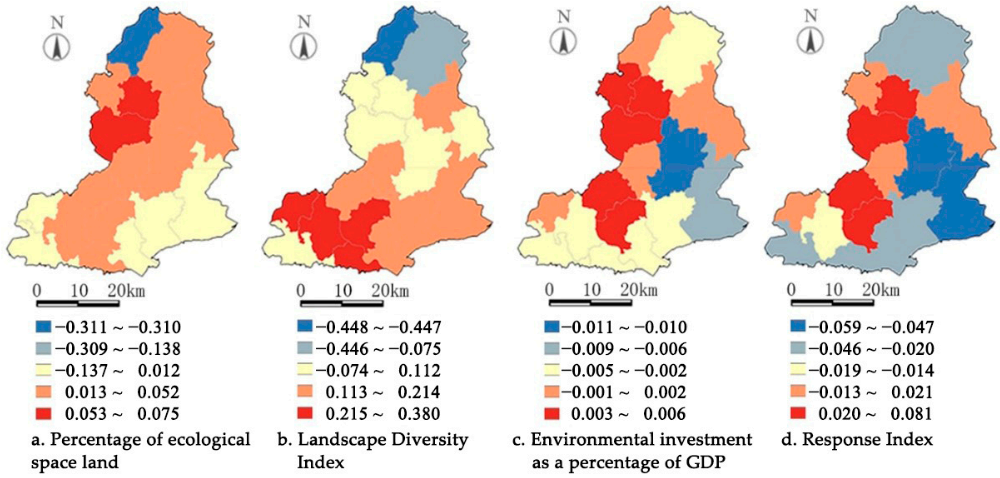

Figure 8. The research area's ecological response indicators throughout time (1990 to 2020).

3.3. Integrated Ecological Risk Driver Analysis

This study used the exploratory regression tool of ArcGIS to screen 12 components of ecological risks as explanatory variables based on 2020 data in order to increase the explanatory power of the GWR model and avoid the issue of the multiple cooccurrence of factors with respect to comprehensive ecological risk, which is the explanatory variable. R2adj was greater than 0.4 in the exploratory regression analysis, while the maximum variance inflation factor value of VIF was lower than 7.5. Finally, four variables were shown to have the strongest explanatory power for ecological risks in the study area. These variables were the urbanization rate, the environmental protection investment-to-GDP ratio, the ecosystem service index, and the ecological space–land use ratio. The GWR model was applied to this information in order to examine and calculate their coefficients (Table 4). The GWR coefficients for the ecological space–land use ratio, ecosystem service index, and the ratio of environmental protection investment to GDP all have mean values that are greater than zero, as observed in Table 4's mean values, indicating that these variables are positively influenced by the integrated ecological risk in the study area. The integrated ecological risk in the research area was more sensitive to changes in the ecological space–land use ratio, as evidenced by the larger mean value of the GWR coefficients for the ecological space–land use ratio. Overall, a negative association drove the impact of the urbanization rate on the integrated ecological risk in the research area.

There are significant regional variations between the drivers and the integrated ecological risk, as observed in the GWR coefficient drivers, and they are both positive and negative (Figure 9). Figure 9a demonstrates that the overall influence of the environmental protection investment to GDP ratio on integrated ecological risk gradually strengthens from the north and south to the center, primarily as a result of economic changes in the research area. The northern part of Pulandian's Tongyi, Anbo, and Shuangta has the highest concentration of positive correlation drives, which are strongly correlated with the region's abundant water and forestry resources and the implementation of pertinent national policies like the closure of mountains to forestry. The areas with the highest GDP in the study area and the most abundant fisheries are Pikou and Chengzitan on the southeast coast, where economic development is accompanied by attention to ecological protection and development to prevent the intensification of ecological risks. These areas also have the strongest negative driving effect. With the southwest showing a strong positive driving correlation and the north (with the same benefits) showing a strong driving negative correlation, it is clear from Figure 9b that the urbanization rate exhibits clear change characteristics with respect to the driving correlation of regional integrated ecological risks. With positively correlated areas in Taiping, Tiexi, and Fengrong with respect to the main urban area, in addition to Pikou and Yangshufang with a high rate of urbanization, the overall driving spatial distribution demonstrates a positive driving effect on regional comprehensive ecological risks. Accordingly, the ecological risk of the area will increase as the rate of urbanization of the population increases, and human-related activities such as industrial construction and economic development are more damaging to the natural ecosystem. With the spatial distribution trend of forested land and grassland–water patches, the spatial share of ecological land has a favorable driving characteristic on regional integrated ecological risks (Figure 9c). The north and northeast regions of the study area are typically significant areas, and the main urban areas of Tiexi and Taiping are significantly more subject to the positive effects of woodlands, waters, and coastal mudflats than the surrounding areas. The Laomao Mountain scenic area, Jiguan Mountain, National Forest park, and Jiulong Mountain scenic area in the north; the scattering of woodlands in the southcentral region; the relative scarcity of woodland resources in the coastal zone area in the southeast; and the severe fragmentation of woodland resources in the main urban area in the southwest are the causes of this phenomenon. The ecosystem service index demonstrates a significant positive driving characteristic for the integrated ecological risk (Figure 9d), which is consistent with the spatial distribution trend of woodland patches in ecological space, and this is observed primarily in the north where woodland resources are abundant, contributing to the maintenance of a number of landscape functions like water connotation, wind and sand control, and biodiversity. The primary cause of this phenomenon is the change in climate, which has a significant negative driving characteristic for integrated ecological risk.

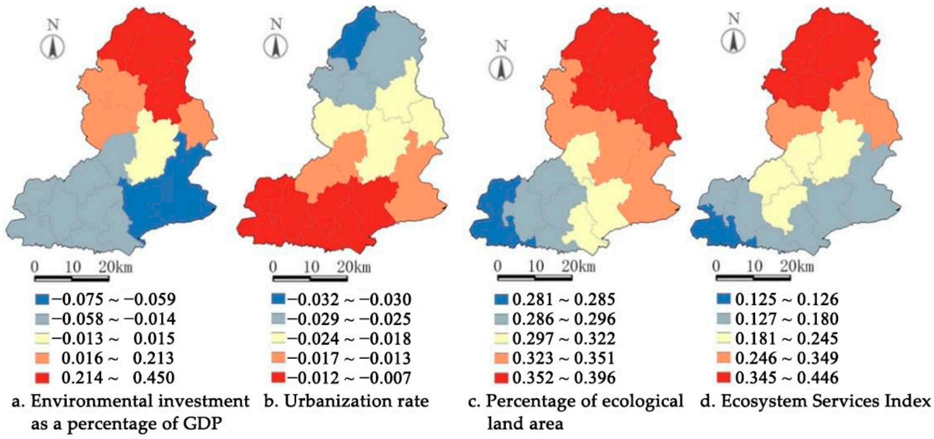

Figure 9. How the research area's key impact components and integrated ecological risks are distributed spatially.

4. Discussion

In the study of the ecological spatial pattern of coastal areas [39], Phillip focused on ecosystem management based on comprehensive ecosystem evaluation and integrated socioeconomic factors; he conducted a study on ecological risk assessments in coastal areas to assist government departments in developing natural disaster prevention and control measures [40]. Some scholars predicted the impact of urban expansion on biodiversity from the spatial pattern of land use [41], the impact of population and economic growth on ecosystems, etc., and early warning mappings were carried out based on the results of ecological security evaluations; moreover, spatial pattern indicators were scientifically constructed as early warning signals for the transformation of ecological conditions.

It can be observed that different ecological land types, such as woodland, grassland, and water, will have different effects on the role of landscape scale, social drivers, and complex ecosystems, and different ecological land types can provide diverse ecosystems by combining the spatial coefficients related to the influence of ecological spatial changes on the amount of change in various ecological risk assessment results. The stability and heterogeneity of the ecosystem can also be altered as a result of changes in the ecological spatial pattern, which would then have an impact on the ecological risk in the Pulandian region. In Pulandian, there are spatial variations exhibiting the same influencing trends with respect to the ecological land area ratio, environmental protection investment-to-GDP ratio, and ecosystem service index on ecological risk, with an easing tendency from northeast to southwest areas. The ecosystem service index is primarily positively impacted by ecological risk, and it exhibits generally positive impacts and a degree of impact that shows a slight weakening tendency from the south of Fengrong, Tiexi, and Pikou to the north. The degree of fragmentation of the ecological spatial pattern affects the study area's economic benefits. Ecological risk assessment can, to some extent, prevent some situations from occurring in the ecological spatial pattern, direct the region toward reasonable land use and development, prevent unrestricted and unplanned resource exploitation, and prevent these situations from occurring. Ecological risk evaluation is comprehensively and scientifically evaluated from ecological, economic, and social aspects using the PSR model to make up for the lack of economic and social dimensions in the landscape pattern index method. Using exploratory regression and geographically weighted regression models to analyze the influencing elements of ecological risk can reflect the spatial difference characteristics and the spatial proximity of regional landscape ecological risk, as well as the influence of the main driving factors, such as the pressure index, the state index, and the effect index. This method can explore the degree of influence of different geographic locations and individual driving factors on ecological risk at the level of the entire country to local areas, and it is also the main direction toward which the future analysis of ecological risk influencing factors is heading. Pulandian district has the potential for development in agriculture, animal husbandry, forestry, and fishing due to its temperate monsoon climate and exceptional geographic environment. Ecological risk assessments as a coastal region can, to a certain extent, help Pulandian district develop pertinent planning programs and policies, regulate and purify the ecological environment, and reasonably develop land resources. These benefits will help Pulandian district prevent serious natural disasters brought on by improper development. As a crucial component of the coastal region's ecological barrier, it can also aid in the formulation of pertinent planning programs and policies.

5. Conclusions

In this study, the Pulandian district in Dalian, a coastal county, was used as an example to measure and analyze the pressure, situation, response, and complete ecological risk of ecological spaces from 1990 to 2020. The conclusions are listed as follows:

(1) An analysis of the characteristics of the ecological spatial pattern's evolution in the study area between 1990 and 2020 was carried out, and the observations include an increase in the main ecological land and a decrease in the area of arable land in Pulandian district; a net increase in the amount of woodland, grassland, and water in the pattern's ecological spatial pattern; and the transfer from coastal mudflats to construction land. This study demonstrates that most ecological space patches are severely fragmented; only the coastal mudflat patches are high overall in terms of fragmentation degree. The degree of fragmentation of water areas tends to be serious, and the degree of ecological space fragmentation in the area near construction land is serious when combined with the landscape index to analyze the change characteristics of ecological space fragmentation and heterogeneity. The overall evolution trend of ecological space is differentiated, and the evolution pattern has a tendency to be fragmented and heterogeneous as a result of the study area's increased infrastructure building, resource consumption, and disregard for long-term land planning.

(2) The evolution of ecological risk over the past 30 years was assessed using the DPS model of the integrated social, economic, and environmental index system, and its weights were determined based on the entropy weighting method and the mean square difference method. The ecological risk index demonstrated a continuously increasing trend, with an increase of 14.14%. In the study area, the high-risk and higher-risk areas displayed a discernible increasing trend, whereas the low-risk areas exhibited a trend that first decreased, increased, and then decreased again. The medium-risk areas displayed a persistently decreasing trend. In particular, in the

southern portion of the study region with areas exhibiting high rates of urbanization, such as Fengrong, Tiexi, and Taiping, the high-risk areas in the study area expanded dramatically by 73.17% over the 30-year period. The state index exhibited a reduction followed by an increase in change, the response index exhibited a decrease followed by an increase in change, and the pressure change in ecological risk exhibited a linear increasing trend. These distributions have a strong relationship relative to the local economy, society, and environment.

(3) The dominant drivers of ecological risk in Pulandian district are urbanization rate, environmental protection investment-to-GDP ratio, ecosystem service index, and ecological space-to-land ratio. This analysis was carried out using exploratory regression analysis and the GWR model. The urbanization rate is among the driving spatial characteristics that are clearly negative, while the ecological space–land use ratio, the ecosystem service index, and the ratio of environmental protection investment to GDP are clearly positive. The ratio of environmental protection investment to GDP has considerable geographical dividing characteristics, while the share of ecological space and the ecosystem service index exhibit clearer block-driving characteristics. The urbanization rate also shows strong band-driving characteristics.

In conclusion, future studies on building land within the high-risk range will focus on ecological environment construction, and local residents are encouraged to protect and restore ecological lands on their own initiative. Future operations related to cultivated land within the high-risk range include preventing or mitigating the occupation and destruction of cultivated land within the red line as much as possible and protecting natural ecosystems. For the protection of forest land, we recommend strengthening the capacity building of the forest resource monitoring team and improving the monitoring and responsibility system of the forest management system while maintaining the original area of natural forests. For the protection of arable land, we recommend actively carrying out soil restoration, improvement, and operations and implementing fallow and crop rotation for arable land. For inland waters, salt flats, mudflats, etc., the comprehensive conservation of river and sea resources and the establishment of a spatial use control system for rivers, lake water, and coastlines are recommended. For the restoration of ecological barrier point areas, arable land, and forest land, measures should be taken to improve the agroecological environment; properly prevent arable land from exceeding overbearing capacities; implement the return of farmland to forests; strengthen the restoration and reconstruction of degraded forests; and transform the ecological barriers of northern mountainous areas into an ecological barrier system with ornamental value by carrying out artificial landscape restoration.

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

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data that support the findings of this study are openly available in National Geographic Information Public Service Platform at https://www.tianditu.gov.cn.

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

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