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Assessing Coastal Ecological Restoration Effectiveness in Qingdao Based on a Multi-Dimensional Entropy-Weighted TOPSIS Model

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Abstract

Coastal ecological restoration is a key approach to enhancing ecosystem resilience; however, the stage-wise evolution of restoration outcomes and the underlying driving mechanisms remain insufficiently quantified. Using Qingdao City as the study area, this research integrates remote sensing inversion, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model, and time-series data from 2010 to 2020 to develop a comprehensive evaluation system for ecological restoration effectiveness, comprising 17 indicators across five dimensions: vegetation, biology, hydrology, economy, and climate. Based on this system, the entropy-weighted method is applied to conduct a dynamic assessment of restoration outcomes. The results indicate that (i) the composite evaluation score in the study area decreased from 0.36 in 2010 to 0.19 in 2015 and then increased to 0.74 in 2020, forming a "V-shaped" nonlinear trajectory with 2015 as a turning point, which is temporally consistent with a delayed response of ecological restoration outcomes following the implementation of major anthropogenic interventions. (ii) Dimension-specific analysis indicates that the decline in the composite score during 2010–2015 was mainly associated with the hydrological dimension, within which chemical oxygen demand (COD) and ammonia nitrogen emissions showed marked increases and were among the highest-weighted indicators. After 2015, following the intensive implementation of regional and system-oriented restoration projects such as the Blue Bay Initiative, pollutant emissions were observed to be effectively controlled, and Bare land area showed a continuous decline. These changes coincided with the rapid rebound of the composite score, within which Bare land area, as the highest-weighted indicator, played a prominent regulatory role. Marked differences were observed among dimensional responses: the biological and vegetation dimensions showed sustained improvement throughout the study period, whereas the hydrological dimension exhibited greater variability over time and stronger temporal alignment with policy-related phases. (iii) Robustness tests indicate that, after completely excluding climate-related variables, the composite score still increased from 0.36 and 0.24 to 0.77, with the "V-shaped" recovery pattern remaining unchanged. This result suggests that the observed improvement in restoration effectiveness in 2020 was more closely associated with systematic human interventions, rather than with short-term climatic fluctuations. This study provides a quantitative and transferable methodological framework for the dynamic evaluation and stage-oriented analysis of coastal ecological restoration effectiveness.

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Keywords: ecological restoration effectiveness evaluation; InVEST model; indicator system; Qingdao; entropy-weighted TOPSIS model

1. Introduction

Coastal ecosystems play vital roles in maintaining biodiversity, buffering natural hazards, and supporting human well-being. However, rapid urbanization and climate change have increasingly degraded their ecological functions. Consequently, coastal ecological restoration projects have become an essential strategy for promoting sustainable development in coastal cities worldwide. Nevertheless, the scientific evaluation of restoration effectiveness continues to face multiple challenges. Most existing studies focus on single ecological dimensions, with limited consideration of coupled social–economic–natural systems. Evaluation approaches often rely on subjectively assigned weights, making it difficult to objectively identify key regulatory factors. Insufficient long-term monitoring further limits the ability to characterize the evolutionary trajectories of restoration outcomes and to examine their temporal consistency with policy interventions.

With China's strategic transition from land-oriented to marine-oriented development and its pursuit of the "deep blue" strategy, the goal of building a strong maritime nation has gained increasing prominence. Within the context of ecological civilization, territorial spatial planning imposes higher standards on marine ecological restoration in terms of scientific rigor, effectiveness, and coordinated land–sea governance [1]. In recent years, environmentally damaging development practices have intensified, underscoring the growing need for coastal ecological restoration projects aimed at restoring and enhancing degraded natural ecosystems [2].

Evaluation frameworks for ecological restoration effectiveness have evolved from early Pressure–State–Response (PSR), Driving force–State–Response (DSR), and Driving force–Pressure–State–Impact–Response (DPSIR) models [3] toward multi-criteria decision-making approaches, such as Multi-Criteria Analysis (MCA) [4]. Researchers have developed evaluation frameworks tailored to different ecosystem types and spatial scales, encompassing ecosystem service assessments, quantitative evaluation methods, soil and water conservation capacity evaluations, full-process frameworks covering "baseline investigation–technology selection–effectiveness assessment," and project performance indicator systems based on the logical framework approach [5–8]. Additionally, indicator systems that integrate ecological–environmental outcomes with engineering–management performance have been established to assess ecological protection and restoration projects [9–12]. Among these approaches, the entropy-weighted TOPSIS–based multi-criteria decision-making model has been successfully applied in ecological studies. For example, Li [13] employed the entropy-weighted TOPSIS method to construct an evaluation model of ecological environmental carrying capacity in the Longquanshan area of Chengdu. Xu et al. [14] developed a sustainability evaluation model for megacities. Du and Gao [15] constructed an ecological security evaluation model for marine aquaculture by integrating the analytic hierarchy process (AHP) with the entropy-weighted TOPSIS method. Zhang et al. [16] applied the entropy-weighted TOPSIS method to ecological environmental assessment in the Chaohu Lake Basin and showed that this approach can enhance the reliability and stability of comprehensive evaluation results by objectively reflecting differences in indicator information. Zhang et al. [17] employed the entropy-weighted TOPSIS method to characterize integrated changes in ecological environmental governance and restoration effectiveness at the regional scale in the Beijing–Tianjin–Hebei urban agglomeration. These studies generally treat the entropy-weighted TOPSIS method as an objective weighting tool that reduces

subjective bias in weight assignment and enhances the comparability and discriminative power of multi-indicator comprehensive evaluations.

Existing studies have conducted systematic evaluations of the effectiveness of the Blue Bay Initiative and coastal ecological restoration from multiple dimensions. For example, a comprehensive evaluation system incorporating 246 indicators was developed for the Blue Bay ecological restoration project to quantitatively assess restoration effectiveness in Yantai City [18], providing a methodological reference for the systematic evaluation of complex restoration programs. Further empirical studies have shown that, within 0–20 years following the implementation of restoration measures, overall ecological recovery levels generally exhibit an increasing tendency over time, as reflected in observed assessment results [19]. Meanwhile, biodiversity indicators show concurrent improvement trends alongside restoration effectiveness, and ecosystem service provision tends to display a generally positive association with restoration duration [20]. Related studies further indicate that the effectiveness of ecological restoration may not be immediately observable, but instead tends to exhibit delayed responses over time, with observed improvement processes showing discernible stage-wise patterns [21]. Most existing studies rely on stage-based comparisons or evaluations at key temporal nodes to describe phase-related variations and potential time-lag features of ecological restoration effectiveness.

Recent advances in remote sensing, GIS, and ecosystem service models have provided multi-source data support for monitoring ecological restoration [22]. In China, indicator systems for artificial coastline enhancement, island ecological restoration, and the Blue Bay Index have been developed for different ecosystem types [23–25]. Multi-dimensional evaluations have focused on biological resources [26] and ecosystem services [27], while esthetic value [28] and public perception [29] have also been recognized as important assessment domains. The application of existing approaches to the coastal zone, which represents an interface region characterized by distinct land–sea interactions, remains limited. In particular, there is a lack of evaluation systems capable of systematically integrating land–sea interactions, characterizing multi-dimensional temporal changes, and informing restoration-related analysis and decision-making. In addition, insufficient long-term monitoring constrains the ability to identify temporal evolution patterns of restoration effectiveness.

As a typical coastal city, Qingdao implemented a series of ecological restoration projects between 2010 and 2020, including shoreline rehabilitation, wetland restoration, and island conservation. The overall systemic effectiveness of these interventions remains insufficiently understood. In particular, the temporal evolution of restoration outcomes, the relative importance of contributing factors, and the ways in which engineering interventions are associated with ecological responses have yet to be clearly characterized.

This study constructs a comprehensive evaluation indicator system tailored to coastal zone characteristics, encompassing five dimensions: Vegetation, Biology, Hydrology, Economy, and Climate. By integrating remote sensing inversion, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model, and the entropy-weighted Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, this study conducts a time-series assessment of ecological restoration effectiveness in the Qingdao coastal zone from 2010 to 2020 and addresses the following three scientific questions.

(1) How can a multi-dimensional indicator system be constructed to support the quantitative assessment of ecological restoration effectiveness over time?
(2) How can data-driven approaches be used to identify key regulatory factors associated with coastal restoration effectiveness and to quantify their relative contributions?
(3) How can the temporal evolution of restoration effectiveness be characterized to examine coupling relationships between engineering interventions and ecological responses?

By addressing these questions, this study aims to develop a transferable evaluation framework for coastal ecological restoration that supports the analysis of temporal changes and provides reference information for adaptive decision-making in ecological governance.

2. Materials and Methods

2.1. Study Area

This study focuses on the coastal zone of Qingdao, China, as the study area (Figure 1). Qingdao is located along the southeastern coast of the Shandong Peninsula and has a mainland coastline of 760.02 km, accounting for approximately one quarter of the total coastline length of Shandong Province. In terms of natural environmental conditions, the study area is jointly influenced by the East Asian monsoon system and marine regulation, which together shape a pronounced monsoonal and maritime climate characterized by distinct seasonal variability; the multi-year mean air temperature is approximately 12.7 °C, while the mean annual precipitation is about 662.1 mm, with rainfall strongly concentrated in summer, as June–August account for roughly 57% of the annual total.

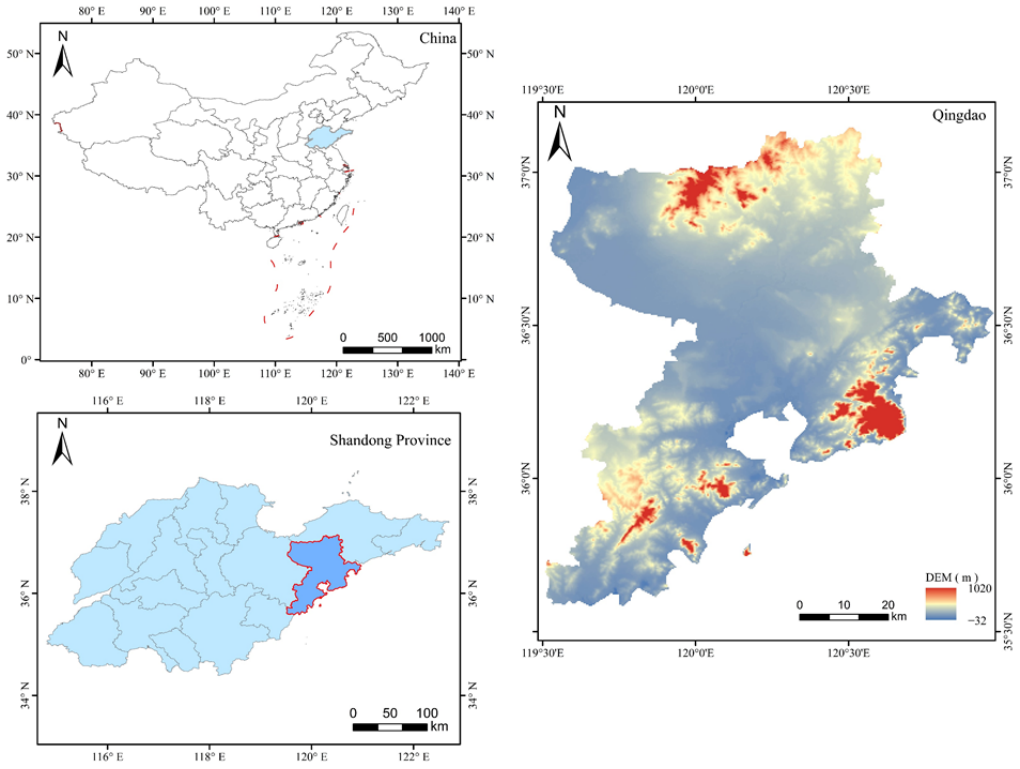


Figure 1. Geographical location map of Qingdao. The blue shading represents Shandong Province, and the red boundary outlines Qingdao Municipality. (authors' original drawing).

As a core coastal city of the Shandong Peninsula, Qingdao exhibits sustained population growth and a high level of urbanization, reflecting its role as a regional economic and demographic center. By the end of 2024, the permanent resident population will reach 10.4425 million, including 8.2358 million urban residents, corresponding to an urbanization rate of 78.87%. In the same year, the gross domestic product (GDP) amounted to 1671.946 billion CNY, with an industrial structure ratio of 3.0:34.2:62.8 for the primary, secondary, and tertiary sectors, respectively, indicating an economic structure dominated by the service sector and supported by manufacturing.

Under the combined influence of rapid urban expansion, industrial development, and population agglomeration, the Qingdao coastal zone represents a typical land–sea interaction ecosystem that is exposed to multiple anthropogenic pressures, including envi-

ronmental pollution, habitat degradation, and biodiversity decline; meanwhile, supported by relatively strong technological capacity, sustained economic investment, and policy initiatives for ecological restoration, the region also possesses a solid foundation for implementing large-scale and systematic coastal restoration programs.

Qingdao exhibits diverse ecosystems, including estuarine wetlands, coastal tidal flats, artificial shorelines, and islands. Since 2010, the region has implemented more than 30 major ecological restoration projects, including shoreline rehabilitation, wetland restoration, and island ecological restoration. Projects under the Blue Bay Initiative have been recognized as national-level exemplary cases (Table A1). The extensive range of restoration practices and the diversity of ecological baseline conditions provide a suitable setting for the development and validation of the evaluation models used in this study.

2.2. Data Source

A multi-source dataset was employed, comprising remote sensing imagery, digital elevation models (DEM), land use data, vegetation cover data, and socioeconomic statistical data. All datasets were spatially registered and clipped to the extent of the Qingdao coastal zone. All spatial indicator data were preprocessed using the WGS_1984 coordinate reference system. Raster datasets were resampled to a uniform spatial resolution and subsequently reprojected. The indicators were then normalized using min–max normalization according to their respective attributes, and the standardized values were used as inputs for the entropy-weighted TOPSIS model. Data were harmonized to three observation years, namely 2010, 2015, and 2020, forming a time-series dataset that integrates ecological, environmental, and economic dimensions (Table 1).

Table 1. Data sources and descriptions.

Data Description	Data Sources	Spatial Resolution	DOI/URL
Administrative boundary	Tianditu	1:250,000	http://www.tianditu.gov.cn
Digital Elevation Mode (DEM)	GEBCO Compilation Group (2023)	15 arc-second	DOI:10.5285/f98b053b-0cbc-6c23-e053-6c86abc0af7b
Vegetation coverage	China regional 250 m fractional vegetation cover data set (2000–2024) [30]	250 m	https://doi.org/10.11888/Terre.tpdc.300330
Land cover	The 30 m annual land cover datasets and their dynamics in China from 1990 to 2020 [31]	30 m	https://doi.org/10.5281/zenodo.5816591
Socioeconomic and environmental statistical indicators	Qingdao Municipal Bureau of Statistics, Qingdao Government Portal	Statistical data	http://qdtj.qingdao.gov.cn/ http://www.qingdao.gov.cn/
Supplementary information	Qingdao Municipal Bureau of Natural Resources and Planning	Statistical data	http://zrzygh.qingdao.gov.cn/

2.3. Methods

A multi-step analytical framework was adopted to systematically evaluate ecological restoration effectiveness in the Qingdao coastal zone from 2010 to 2020, comprising the following steps: (1) Derivation of ecological indicators, including vegetation coverage, land use, and habitat quality, from multi-source remote sensing data. (2) Construction of a five-dimensional indicator system encompassing Vegetation, Biology, Hydrology, Economy, and Climate by integrating socioeconomic statistics. (3) Determination of objective weights using the entropy-weight method, followed by comprehensive evaluation with the

TOPSIS model. (4) Application of land-use transition matrices and time-series analysis to characterize spatiotemporal evolution patterns. The technical workflow is illustrated in Figure 2.

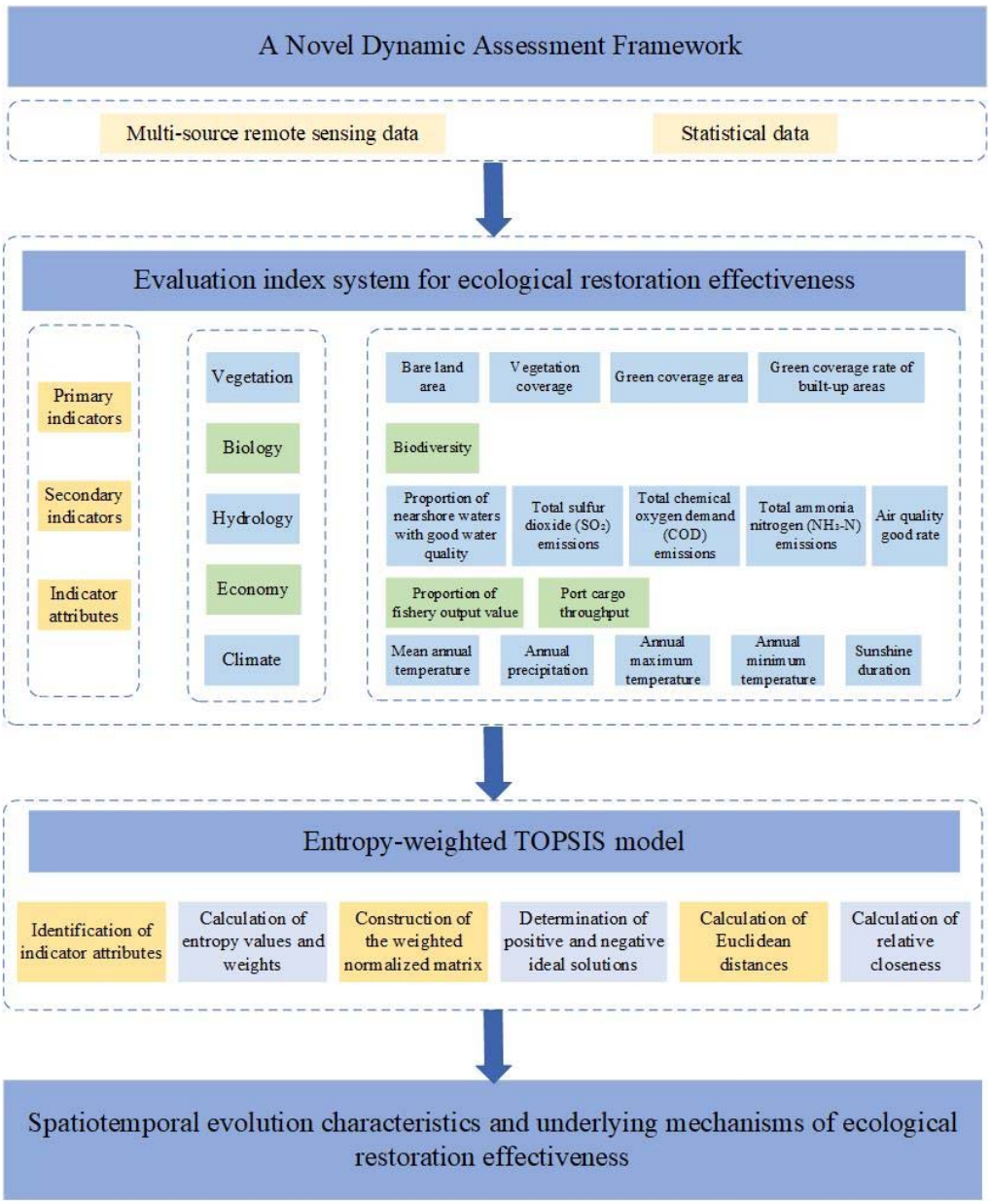


Figure 2. Technical workflow of the study. (Colors are used for visual distinction only).

2.3.1. Habitat Quality

Habitat quality, reflecting biodiversity and habitat suitability, was calculated using the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model (Natural Capital Project, Stanford University, Stanford, CA, USA) (hereafter referred to as the HQ model) to characterize the condition of biological habitats. Compared with models such as the Social Values for Ecosystem Services (SolVES) model [32] and the Maximum Entropy (MaxEnt) model [33], this approach is relatively well established for habitat quality evaluation and has been widely applied in assessments of ecological restoration effectiveness [34–37], enabling the characterization of structural and functional changes in coastal ecosystems during the restoration process. According to the InVEST model, habitat degradation was estimated based on land use data for 2010, 2015, and 2020 as follows:

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Y} \left[\frac{\omega_r}{\sum_{r=1}^{R} \omega_r} \right] r_y i_{rxy} \beta_x S_{jr} \quad (1)$$

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{r\max}} \right) \text{(Linear)} \quad (2)$$

$$i_{rxy} = \exp\left(-\frac{2.99 d_{xy}}{d_{r\max}} \right) \text{(Exponential)} \quad (3)$$

where r denotes the threat factor, and R represents the total number of threat sources; y indicates the number of grid cells affected by threat factor r, and Y corresponds to the number of grid cells occupied by the threat source. The parameter ω_r refers to the weight of threat factor r, with values ranging from 0 to 1, while r_y describes the number of occurrences of threat factor r within a single grid cell. The term i_{rxy} represents the effective influence range of the threat factor, and β_x denotes the accessibility coefficient, here set as $\beta_x = 1$. Furthermore, S_{jr} indicates the sensitivity of the land-use type j to the threat factor r; d_{xy} is the linear distance between grid cell x and grid cell y; d_{rmax} defines the maximum effective distance of threat factor [38].

The grid-level habitat degradation score was transformed into the habitat quality score using a half-saturation constant, as follows:

$$Q_{xj} = H_j \left\{ 1 - \left(\frac{D_{xj}^z}{D_{xj}^z + K^z} \right) \right\} \quad (4)$$

where Q_{xj} denotes the habitat quality index, H_j represents the habitat suitability of land-use type j, D_{xj} refers to the habitat degradation of grid cell x, z is the normalization constant, and K is the half-saturation coefficient [38], which was set to the default value of 0.5 as specified in the InVEST user manual.

The land-use types listed in Table 2 provide the basis for assigning habitat suitability and threat sensitivity parameters in the Habitat Quality (HQ) model. Land-cover types with stronger ecological functions (e.g., forests, grasslands, and waters) are assigned higher habitat suitability values, whereas built-up land and bare land are regarded as unsuitable habitats. On this basis, the model further treats cropland and built-up land as threat sources, accounting for their cumulative impacts on surrounding habitat quality and assuming that threat effects gradually decay with increasing distance. By integrating land-cover composition with the intensity of surrounding disturbances, the Habitat Quality (HQ) model is able to characterize the spatial heterogeneity of habitat quality during the ecological restoration process.

Table 2. Habitat suitability and sensitivity to threat factors.

Land Use Type	Habitat Suitability	Farm Land	Construction Land
Farm land	1	0.3	0.6
Forest	1	0.3	0.5
Grassland	0.8	0.5	0.6
Waters	0.9	0.6	0.7
Bare land	0	0	0
Built-up land	0	0	0

Farmland and built-up land were selected as threat factors, with their corresponding maximum impact distances, weights, and decay types summarized in Table 3.

Table 3. Threat-factor parameters.

Threat Factors	Maximum Impact Distance/km	Weight	Attenuation Type
Farm land	4	0.6	linear
Built-up land	6	1	exponential

2.3.2. Vegetation Coverage

Fractional vegetation cover (*FVC*) was estimated using a pixel-based dichotomous model and serves as an important indicator for characterizing the recovery of ecosystem structure and function.

$$FVC = (NDVI - NDVI_{soil})/(NDVI_{veg} - NDVI) \quad (5)$$

where FVC denotes the fractional vegetation cover, with values ranging from 0 to 1; $NDVI_{soil}$ and $NDVI_{veg}$ represent $NDVI$ values for bare soil and fully vegetated pixels [39].

August data were used for each study year to better represent surface vegetation conditions. Raw data values were normalized to a range of 0–1. Vegetation cover was then classified into five levels: very low cover (0–0.1), low cover (0.1–0.3), medium cover (0.3–0.5), medium-high cover (0.5–0.7), and high cover (0.7–1.0). Waters without vegetation were assigned an FVC value of 0.

2.3.3. Land-Use Transition Matrix

Land-use transition reflects changes in surface cover associated with human activities and ecological restoration measures and provides an important basis for evaluating restoration effectiveness. It was quantified using a transition matrix among different land-use types.

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & \dots & S_{1n} \\ S_{21} & S_{22} & \dots & S_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ S_{n1} & S_{n2} & \dots & S_{nn} \end{bmatrix} \quad (6)$$

where S represents the area, n represents the total number of land-use types, i refers to the land-use type at the beginning of the study period, and j is the land-use type at the end of the study period [40].

2.3.4. Entropy-Weighted TOPSIS Model

To reduce potential subjectivity in weight assignment, the entropy-weight method was combined with the TOPSIS model to calculate the comprehensive closeness coefficient of ecological restoration effectiveness [41]. The specific procedures of the entropy-weighted TOPSIS method are as follows:

(1) Construction of the original data matrix and normalization of positive and negative indicators.

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} (\text{Positive indicator}) \quad (7)$$

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} (\text{Negative indicator}) \quad (8)$$

(2) Calculation of the entropy value e_j and the weight w_j:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln p_{ij} \quad (9)$$

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n}(1 - e_j)} \tag{10}$$

$$p_{ij} = x'_{ij} / \sum_{i=1}^{m} x'_{ij} \tag{11}$$

where m denotes the number of evaluation years and n represents the number of indicators.

(3) Construction of the weighted normalized decision matrix.

$$V = (v_{ij})_{m \times n} \tag{12}$$

$$v_{ij} = w_j \times x'_{ij} \tag{13}$$

(4) Determination of positive and negative ideal solutions. A^+, A^-.

$$A^+ = (\max v_{1j}, \max v_{2j}, \ldots, \max v_{nj}), A^- = (\min v_{1j}, \min v_{2j}, \ldots, \min v_{nj}) \tag{14}$$

(5) Calculation of Euclidean distances D_i^+, D_i^-.

$$D_i^+ = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^+)^2} \tag{15}$$

$$D_i^- = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^-)^2} \tag{16}$$

(6) Calculation of the relative closeness coefficient Si, which ranges from 0 to 1. A larger Si value indicates a higher level of ecological restoration effectiveness.

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{17}$$

3. Construction of the Ecological Restoration Effectiveness Evaluation System

3.1. Indicator Selection Principles

Indicator selection followed the principles of scientific rigor, representativeness, and operability, with reference to relevant national guidelines [42]. Ecological restoration evaluation typically encompasses ecological, economic, and social benefits, with particular emphasis on vegetation coverage, environmental quality, and biodiversity [43]. Building green coverage rate and green coverage area have been shown to be positively correlated with urban ecological quality [44], while urban greening plays a beneficial role in temperature regulation and air quality improvement [45]. Dense tree cover exhibits pronounced cooling effects across all seasons [46], and vegetation cover growth is jointly driven by solar radiation, temperature, and precipitation, contributing to measurable improvements in ecological restoration outcomes [47]. Wetland restoration is associated with improvements in fish habitat conditions and provides support for fishery recovery [48]. Accordingly, an indicator system was built across five dimensions: Vegetation, Biology, Hydrology, Economy, and Climate.

3.2. Evaluation System Construction

Based on the characteristics of marine ecological restoration projects in Qingdao, seventeen indicators were selected (Table 4). The Vegetation dimension includes bare land area (negative), vegetation coverage, green coverage area, and green coverage rate of built-up areas. The Biology dimension is represented by biodiversity indicators, which characterize ecosystem functional integrity and habitat quality. The Hydrology dimension covers indicators related to environmental quality and pollutant emissions, including the proportion of nearshore waters meeting quality standards, total sulfur dioxide (SO_2) emissions, total

chemical oxygen demand (COD) emissions, total ammonia nitrogen (NH_3–N) emissions, and the air quality good rate. Together, these indicators characterize changes in pollution conditions. The Economy dimension includes the proportion of fishery output value and port cargo throughput, reflecting potential associations between ecological restoration and changes in the structure and development patterns of the marine economy. The Climate dimension includes mean air temperature, precipitation, extreme temperature, and sunshine duration, and is used to examine the potential facilitating or constraining roles of climatic conditions in relation to ecological restoration effectiveness under a changing climate.

Table 4. Index system for evaluating ecological restoration effectiveness.

First-Level Indicators	Secondary Indicators	Properties
Vegetation	Bare land area	Negative
	Vegetation coverage	Positive
	Green coverage area (hectares)	Positive
	Green coverage rate of built-up areas (%)	Positive
Biology	Biodiversity	Positive
Economy	Proportion of fishery output value (%)	Positive
	Port cargo throughput (10,000 tons)	Positive
Hydrology	Air quality good rate (%)	Positive
	Proportion of nearshore waters meeting quality standards (%)	Positive
	Total sulfur dioxide (SO_2) emissions (tons)	Negative
	Total chemical oxygen demand COD emissions (tons)	Negative
	Total ammonia nitrogen (NH_3-N) emissions (tons)	Negative
Climate	Mean annual temperature (°C)	Negative
	Annual precipitation (mm)	Positive
	Annual maximum temperature (°C)	Negative
	Annual minimum temperature (°C)	Negative
	Sunshine duration (hours/year)	Positive

In multi-indicator comprehensive evaluations of ecological restoration effectiveness, different indicators may exhibit varying influence directions on restoration outcomes [49]. The distinction between benefit-type and cost-type indicators is established according to whether an increase in an indicator promotes or constrains the overall evaluation objective, instead of reflecting its direct environmental impact. To ensure directional consistency in the subsequent TOPSIS analysis, indicators in the study area were classified into positive (benefit-type) and negative (cost-type). For positive indicators, larger values reflect better restoration performance, whereas for negative indicators, lower values correspond to more favorable outcomes.

3.3. Localization of Indicators

As a typical coastal city and a core area of the Shandong Peninsula Blue Economic Zone, Qingdao's ecological restoration projects focus on coastal zones, estuaries, and wetland systems characterized by strong interactions between land and sea as well as close social–ecological coupling. To enhance the regional relevance of the evaluation system, economic indicators, including port cargo throughput and the proportion of fishery output value, were incorporated to represent interactions related to the marine economy. Coastal environmental indicators specific to the study area, such as nearshore water quality, were emphasized, and local climatic factors were included to examine the role of natural conditions. Overall, this system facilitates the assessment of restoration conditions in Qingdao and provides methodological reference for studies in other coastal regions.

4. Results and Discussion

4.1. Variation Characteristics of Indicators Across Dimensions

4.1.1. Vegetation

Vegetation indicators exhibited changes in spatial distribution and overall structure (Figure 3). The green coverage area increased continuously from 19,203 ha in 2010 to 45,263 ha in 2020. The green coverage rate of built-up areas exhibited a shallow V-shaped pattern, declining by 3.94 percentage points by 2015 and subsequently recovering to approximately 41% by 2020. Overall vegetation coverage remained high and relatively stable, with the proportion of medium-to-high coverage areas decreasing slightly from 99.08% in 2010 to 98.67% in 2020. Bare land area decreased by 0.02% between 2015 and 2020, indicating a reduction in surface exposure during this period.

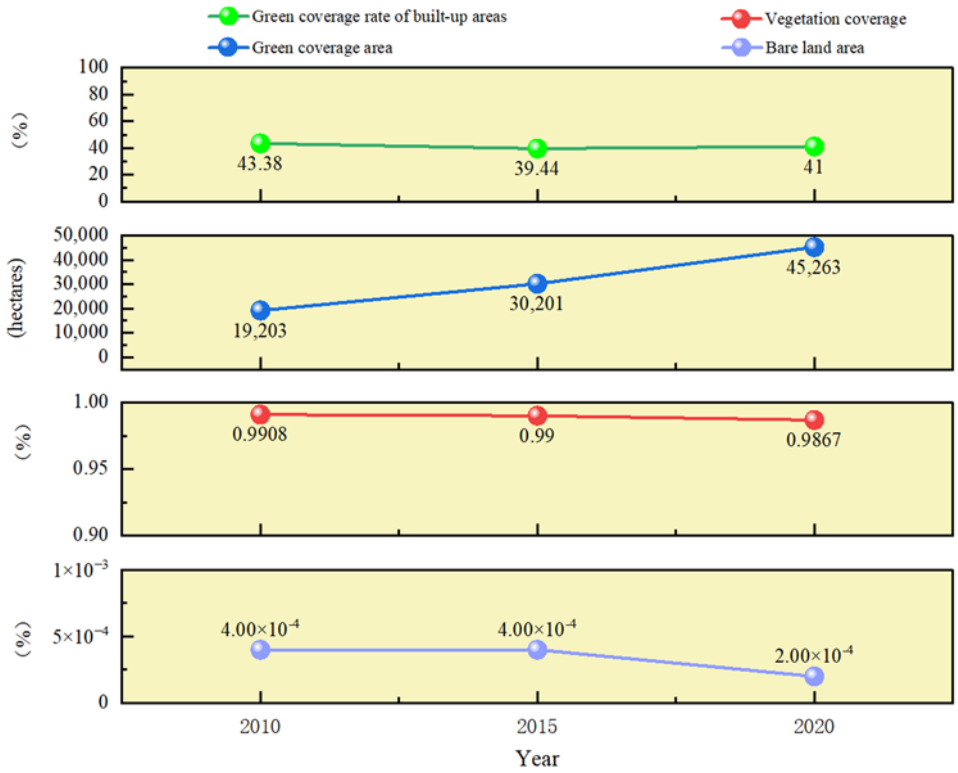
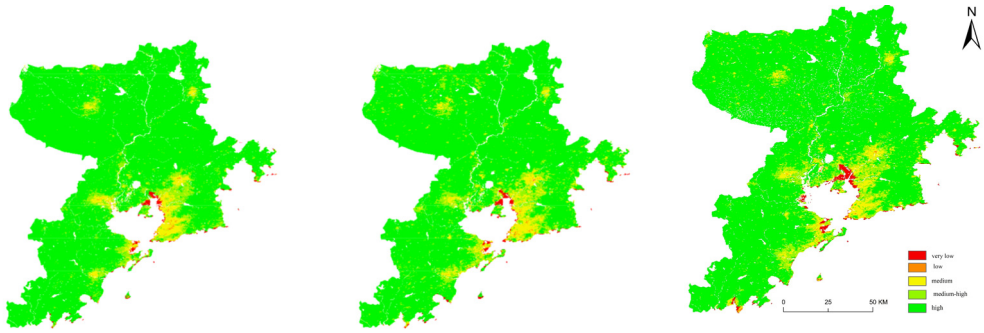


Figure 3. Changes in vegetation-related indicators (2010–2020).

Vegetation class structure exhibited increased heterogeneity (Figure 4, Table 5). High-coverage areas consistently dominated the landscape, accounting for more than 84% of the total area, although their overall proportion declined by 3.17%. A cumulative increase of 2.21% was observed in medium-to-high coverage areas. This change indicates a shift in the distribution of vegetation coverage toward a more balanced pattern. In contrast, areas with very low and low coverage remained largely stable and accounted for only a small proportion of the total area.

Table 5. Vegetation coverage class changes from 2010 to 2020.

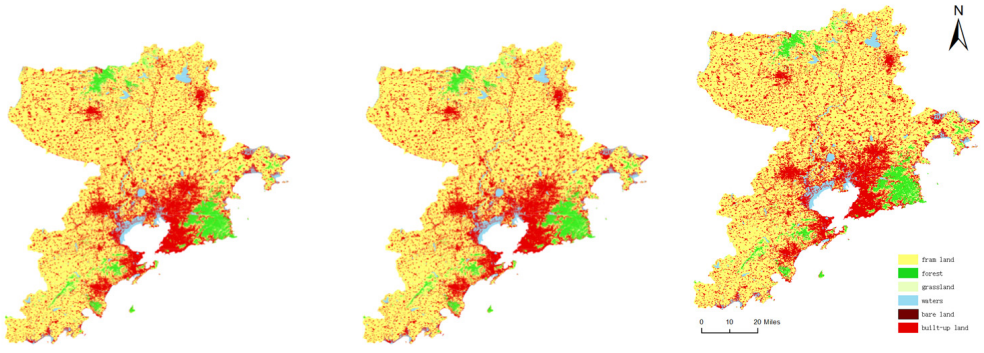
	2010	2015	2020
Very low	0.70%	0.77%	1.10%
Low	0.22%	0.23%	0.23%
Medium	3.45%	4.24%	4.00%
Medium-high	7.49%	9.81%	9.70%
High	88.14%	84.95%	84.97%



(a) (b) (c)

Figure 4. Vegetation coverage in August (**a**) 2010, (**b**) 2015, and (**c**) 2020.

Distinct land-use changes were observed during the study period (Figure 5, Table 6), characterized by changes in the extent of adjacent land-use units. Notably, the proportion and spatial density of built-up land increased continuously over the study period. Development was initially concentrated on the seaward side of the coastal zone and subsequently expanded inland. Across the three study periods from 2010 to 2020, noticeable spatial changes in land-use patterns were observed. Farmland remained the dominant land-use type, accounting for approximately 66% of the total area in 2020, followed by built-up land at about 27%, forest land at around 5%, and waters, grassland, and bare land combined at approximately 2%. Over the study period, the areas of farmland, grassland, waters, and bare land declined, whereas forest land and built-up land increased steadily. The conversion from farmland to built-up land was most pronounced during 2010 to 2015, corresponding to a period of more rapid expansion of built-up land (Figure 5).



(a) (b) (c)

Figure 5. Land use in (**a**) 2010, (**b**) 2015, and (**c**) 2020.

Table 6. Proportion of different land types from 2010 to 2020.

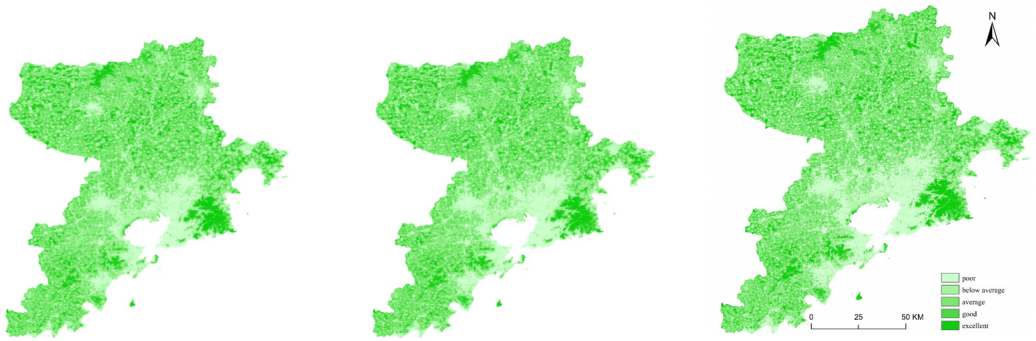
	2010	2015	2020
Fram land	68.60%	66.79%	65.70%
Forest	4.33%	4.61%	4.70%
Grassland	0.46%	0.42%	0.26%
Waters	3.45%	2.54%	2.07%
Bare land	0.04%	0.04%	0.02%
Built-up land	23.12%	25.61%	27.25%

Land-use changes further elucidate the background conditions and pressures influencing vegetation recovery (Figure 5; Table 6). The proportion of built-up land increased steadily from 23.12% to 27.25%, showing a spatial pattern of expansion from an initial

concentration along the coast toward inland areas. Farmland remained the dominant and widely distributed land-use type, while its proportion declined from 68.60% to 65.70%, corresponding to a substantial contribution to land-use conversion during the study period. In contrast, forest area increased slightly from 4.33% to 4.70%, whereas the proportions of grassland, waters, and bare land all declined. The conversion of farmland to built-up land was most pronounced during 2010 to 2015, corresponding to a period characterized by relatively intense expansion of built-up land and increased pressure on ecological space (Figure 5). Subsequently, during the period of systematic implementation of ecological restoration projects, bare land continued to decline while forest area expanded, corresponding to a gradual shift in land-cover composition toward more ecologically oriented patterns.

4.1.2. Biology

The biology dimension was assessed using the Habitat Quality (HQ) index derived from the InVEST model, with biodiversity serving as the core indicator. HQ values, ranging from 0 to 1 with higher values indicating better habitat quality, for 2010, 2015, and 2020 were classified into five levels using the natural breaks method: poor (0–0.30), below average (0.30–0.44), average (0.44–0.56), good (0.56–0.62), and excellent (>0.62). The spatial distribution and proportional composition of these classes are shown in Figure 6 and Table 7.



(**a**) (**b**) (**c**)

Figure 6. Habitat quality index levels in (**a**) 2010, (**b**) 2015, and (**c**) 2020.

Table 7. Habitat quality class areas and changes from 2010 to 2020.

Habitat Level	2010		2015		2020		2010–2020
	Area/km^2	%	Area/km^2	%	Area/km^2	%	Change Area/km^2
poor	0.00	0.00%	0.00	0.00%	0.00	0.00%	0.00
below average	504.15	4.46%	401.87	3.56%	315.32	2.79%	188.83
average	6587.68	58.33%	6718.26	59.49%	6992.03	61.91%	404.35
good	3272.06	28.97%	3175.18	28.12%	3086.51	27.33%	185.55
excellent	929.11	8.23%	997.69	8.83%	899.15	7.96%	29.97

The overall spatial distribution pattern of habitat quality remained relatively stable throughout the study period, while the areas and proportions of different habitat quality classes exhibited noticeable changes, indicating a gradual temporal reconfiguration of the internal habitat quality structure within the study area. The average class expanded continuously, its proportion increasing from 58.33% to 61.91% (a net gain of 404.35 km^2, the largest expansion). Conversely, the below-average class decreased markedly from 4.46% to 2.79% (net loss: 188.83 km^2). The good class declined slightly (28.97% to 27.33%). The excellent class fluctuated, ending at 7.96% (from 8.23%), showing the smallest net change (loss of 29.97 km^2).

These shifts reflect a reorganization of habitat quality structure from 2010 to 2020, characterized by an expansion of the average class and slight reductions in the below average and good classes. The conversion of substantial areas from the below-average class to the average class reflects an improvement in overall habitat conditions and a redistribution of habitat quality levels. The area of the excellent class changed only marginally, while the expansion of the average class provided a broader spatial basis for subsequent changes in biodiversity indicators and ecosystem service conditions. This structural transition shows spatiotemporal correspondence with the implementation of ecological restoration measures, including vegetation restoration and pollution control.

4.1.3. Economy

The economic dimension was assessed using two indicators in the context of ecological restoration: port cargo throughput and the proportion of fishery output value within the total output of agriculture, forestry, animal husbandry, and fishery (Figure 7). From 2010 to 2020, port cargo throughput increased continuously from 3501.2 to 6045.9 million tons. The growth rate during 2015–2020 was lower than that observed during the preceding five-year period, corresponding to a change in the pace of port development.

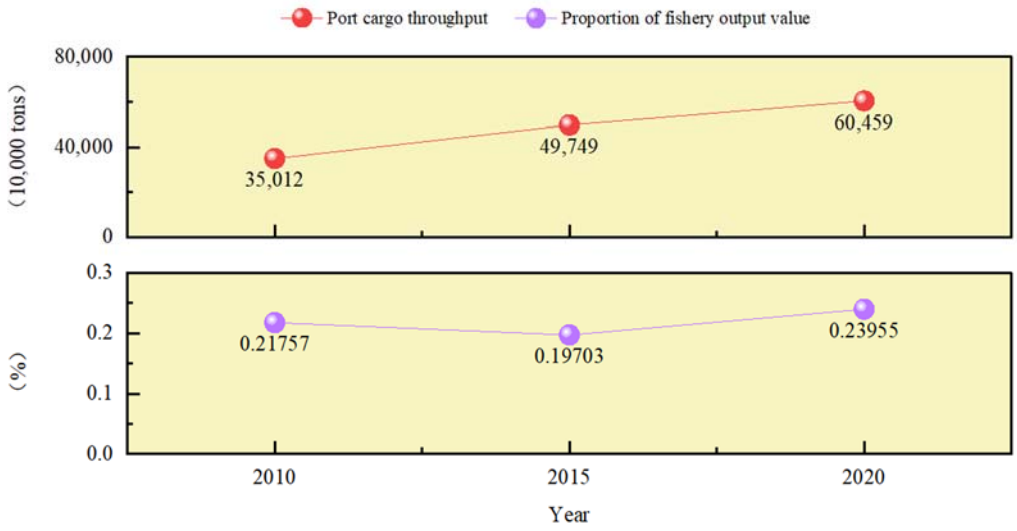


Figure 7. Changes in economic indicators from 2010 to 2020.

Concurrently, the proportion of fishery output value exhibited a distinct V-shaped pattern, declining to 19.70% in 2015 before rebounding to 23.96% in 2020. This recovery occurred during a period characterized by improvements in hydrological conditions and the progression of wetland restoration projects, showing temporal correspondence with changes in nearshore water quality and habitat conditions.

During the period of systematic implementation of ecological restoration measures, the Qingdao coastal zone experienced continued growth in port-related economic activities alongside a recovery in the ecosystem-dependent fishery sector. This pattern reflects the concurrent development of ecological restoration efforts and changes in industrial structure over the study period.

4.1.4. Hydrology

Changes in hydrological indicators exhibited clear stage-related variation over the study period (Figure 8). Pollutant emissions showed an overall "increase–then–decrease" pattern. Total emissions of ammonia nitrogen and chemical oxygen demand (COD) increased markedly by 50.9% and 208.1%, respectively, from 2010 to 2015, and then declined after 2015, falling below their initial levels by 2020. In contrast, total sulfur dioxide (SO_2)

emissions decreased continuously throughout the study period, with a more pronounced reduction observed after 2015.

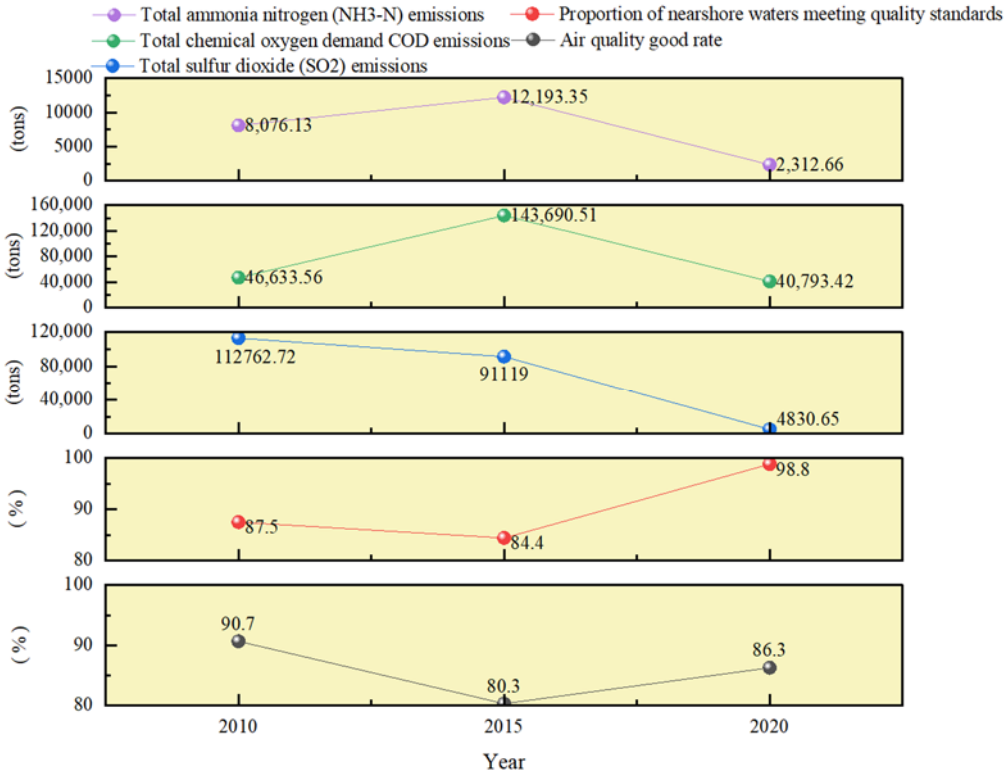


Figure 8. Changes in hydrological indicators from 2010 to 2020.

Environmental quality indicators exhibited a similar pattern of temporal variation over the study period. The proportion of nearshore waters meeting quality standards declined in 2015 and subsequently increased to 98.8% by 2020. Likewise, the air quality good rate decreased by 10.4 percentage points before partially recovering by approximately 6 percentage points in the later period.

An inverse pattern between pollutant emissions and environmental quality was observed over the study period, with changes around 2015 corresponding to a shift in overall pollution dynamics. After 2015, major pollutants such as COD declined markedly, occurring alongside improvements in nearshore water quality and air quality indicators. These concurrent changes temporally coincided with the implementation of the Blue Bay Initiative and other coastal ecological restoration projects.

4.1.5. Climate

Climatic changes constituted an important environmental context for ecological restoration during the study period (Figure 9). From 2010 to 2020, the study region exhibited overall increasing trends in temperature, precipitation, and sunshine duration. The annual mean air temperature increased continuously over this period, with a cumulative rise of 1.1 °C. Annual precipitation decreased by 292.7 mm between 2010 and 2015, followed by a substantial increase of 672.6 mm from 2015 to 2020. Over the same period, sunshine duration showed a marked overall increase, with a cumulative rise of 524 h per year. In addition, variations in extreme temperature indicators were observed: the annual maximum temperature declined by 2.8 °C in the later stage of the study period, while the annual minimum temperature, although relatively high in 2015, exhibited a comparatively narrower range of fluctuation overall.

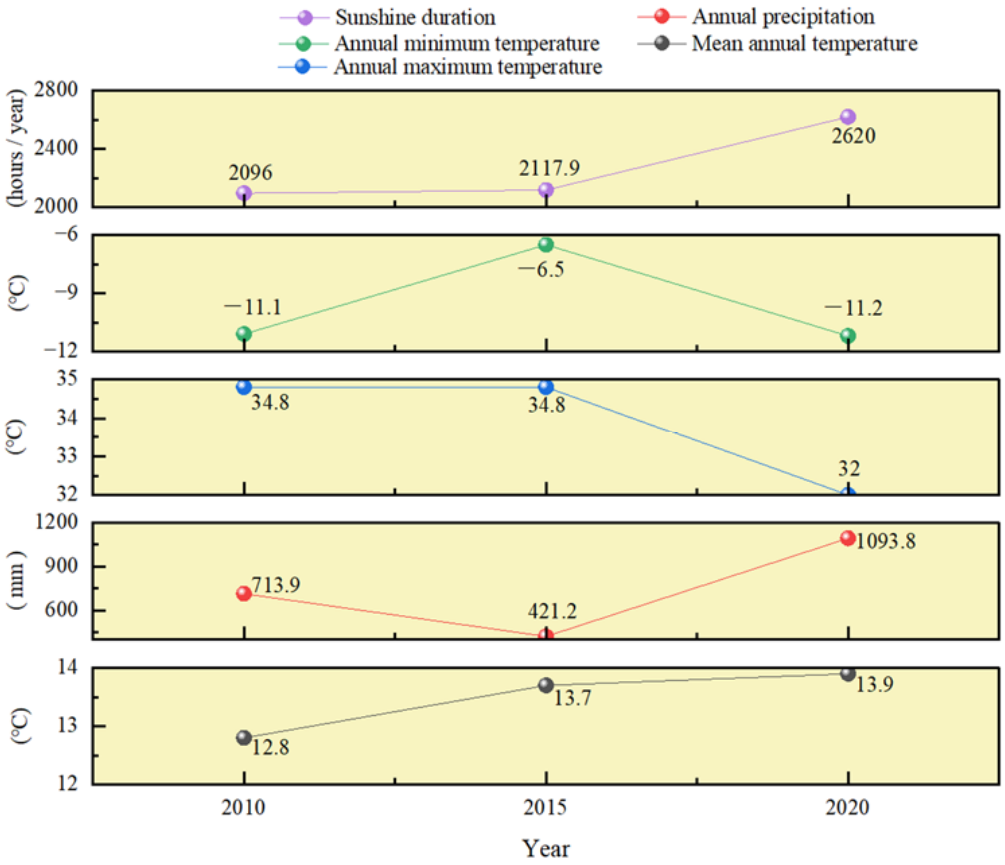


Figure 9. Changes in climate indicators from 2010 to 2020.

These concurrent changes in hydrothermal conditions, particularly increases in precipitation and sunshine duration, were associated with more favorable climatic conditions during the study period. Such conditions provided a broader environmental context within which vegetation dynamics and ecosystem productivity were observed alongside artificial restoration measures. Persistent warming trends may intensify evaporation and alter the distribution of suitable habitats for different species, which could introduce potential risks to the long-term stability of coastal ecosystems. In this context, both the potential benefits and challenges associated with climate change warrant consideration in the assessment and planning of ecological restoration initiatives.

4.2. Comprehensive Evaluation Results

In this study, all indicators were categorized as either positive (benefit-type) or negative (cost-type) attributes and were normalized using the corresponding formulas. Indicator weights were then calculated using the entropy weight method (Table 8). Among all indicators, annual maximum temperature and bare land area received the highest weights (both 0.1091), reflecting relatively greater variability across evaluation units and a higher contribution to the composite weighting structure. Bare land area, as a negative indicator, exhibited the highest coefficient of variation among all indicators. Variations in this indicator were closely associated with changes in surface exposure conditions and levels of human disturbance, resulting in a relatively prominent contribution to the evaluation of the Vegetation and Biology dimensions. In contrast, indicators such as annual minimum temperature had comparatively lower weights (0.0403), indicating that their interannual variability contributed less to the overall composite assessment of restoration effectiveness.

Table 8. Each indicator and its calculated weight.

Indicators	Indicator Properties	Weight
Bare land area	Negative	0.1091
Vegetation coverage	Positive	0.0408
Green coverage area (hectares)	Positive	0.0487
Green coverage rate of built-up areas (%)	Positive	0.0499
Biodiversity	Positive	0.0447
Proportion of fishery output value (%)	Positive	0.0464
Port cargo throughput (10,000 tons)	Positive	0.0438
Air quality good rate (%)	Positive	0.0439
Proportion of nearshore waters meeting quality standards (%)	Positive	0.0627
Total sulfur dioxide (SO_2) emissions (tons)	Negative	0.0643
Total chemical oxygen demand COD emissions (tons)	Negative	0.0403
Total ammonia nitrogen (NH_3-N) emissions (tons)	Negative	0.0489
Mean annual temperature (°C)	Negative	0.0665
Annual precipitation (mm)	Positive	0.0482
Annual maximum temperature (°C)	Negative	0.1091
Annual minimum temperature (°C)	Negative	0.0403
Sunshine duration (hours/year)	Positive	0.0924

The comprehensive evaluation results based on the TOPSIS model (Figure 10) showed a distinct V-shaped nonlinear pattern in Qingdao's overall ecological restoration score. The score decreased from 0.36 in 2010 to 0.19 in 2015 and subsequently increased to 0.74 by 2020. After reaching its minimum in 2015, the comprehensive closeness coefficient increased markedly to 0.74 by 2020, corresponding to an overall increase of 289%. In contrast, the scores of the Biology and Vegetation dimensions exhibited continuous upward trends throughout the study period, reflecting relatively stable changes in indicators related to ecological structure and primary productivity. To examine whether the above results were influenced by the relatively high weights assigned to climate variables, a robustness test was conducted by excluding all climate-related indicators while keeping the social, economic, and ecological–environmental indicators unchanged. The comprehensive scores were then recalculated using the entropy-weighted TOPSIS method. The results show that, after excluding climate variables, the temporal pattern of the comprehensive evaluation remained consistent, with 2015 still representing a low point and a clear increase observed in 2020. The characteristic V-shaped trajectory therefore persisted, indicating that the stage-wise changes in overall restoration effectiveness were not solely associated with climatic variables.

This divergence can be attributed to differences in the sensitivity of indicators across dimensions to changes in human activities and natural background conditions. During 2010 to 2015, periods of urban expansion, elevated pollutant emissions, and less favorable climatic conditions coincided with declines in several environmental and economic indicators. Key declines were observed in the urban green coverage rate, which decreased from 43.48% to 39.44%, vegetation coverage, which declined from 99.08% to 99.00%, the air quality good rate, which fell by 10.4 percentage points, and the proportion of nearshore waters meeting quality standards, which decreased by 3.1 percentage points. Concurrent increases in total COD and ammonia nitrogen emissions, together with decreased precipitation, a rise in the annual minimum temperature, and a declining proportion of fishery output value, were observed during this phase and coincided with the overall decrease in the comprehensive score.

After 2015, the implementation of systematic restoration initiatives, including the Blue Bay program, coincided with reductions in pollutant emissions and improvements in both water and air quality. During the same period, decreases in bare land area and increases in green coverage were observed alongside a substantial rise in the overall restoration effectiveness score. Minor fluctuations persisted in some indicators, such as vegetation coverage and air temperature. At the same time, the overall pattern highlights the temporal corre-

spondence between changes in multiple indicators and the implementation of coordinated governance measures and targeted restoration projects during the study period.

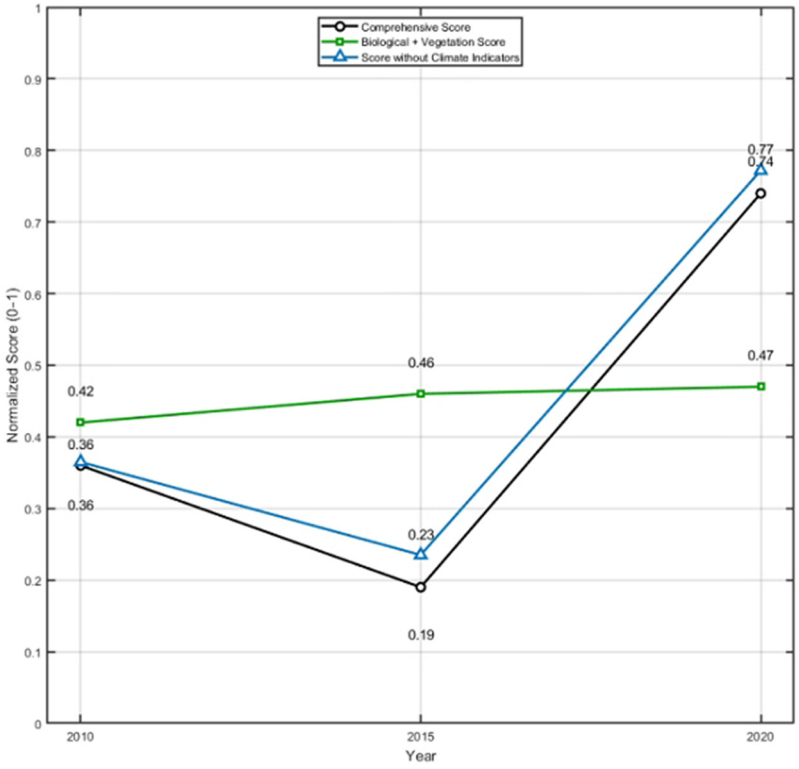


Figure 10. Score Comparison under Three Scenarios.

4.3. Discussion

Through the application of a multidimensional indicator system and a long-term assessment framework, this study characterizes the stage-specific evolution and structural features of ecological restoration effectiveness in the Qingdao coastal zone from 2010 to 2020. The stage-wise changes in key indicators were examined alongside the implementation timelines of major ecological restoration projects (Appendix A), providing a qualitative context for exploring hypothesized associations between governance interventions and ecological responses. The observed relationships are interpreted as stage-wise correspondences based on qualitative project timelines rather than as causal relationships. The year 2015 represents a notable temporal inflection point, after which restoration effectiveness increased alongside concurrent improvements across multiple environmental indicators. This transition reflects temporal adjustment processes observed during ecological restoration and underscores the coexistence of changes in natural conditions and socioeconomic factors over the course of coastal ecological recovery.

The declining trend observed during 2010–2015 coincided temporally with several identifiable anthropogenic disturbance events occurring over the same period. In particular, periods characterized by large-scale industrial relocation and port-related construction activities, including the environmental relocation of major steel enterprises and the expansion of port-based chemical industrial zones, were associated with temporary increases in bare land area and changes in the extent of built-up land. Meanwhile, ongoing land reclamation activities in Jiaozhou Bay were associated with reductions in wetland and nearshore ecological spaces. These processes coincided with episodes of severe air pollution during the winter of 2015 and relatively low precipitation levels, occurring alongside short-term changes in vegetation, hydrological conditions, and biodiversity-related indicators.

By combining an indicator system grounded in the DPSIR concept with the entropy-weighted TOPSIS method, dominant indicators and their positive and negative contributions across different governance stages can be examined and compared. Decomposing the composite score into indicator-level contributions allows for an examination of the relative roles of different indicators across governance stages. Furthermore, robustness tests conducted by excluding climate variables show that the main analytical patterns remain broadly consistent, suggesting that the results are not entirely attributable to background environmental variability alone. This also indicates that the analytical outcomes extend beyond those typically captured by traditional DPSIR-based evaluation approaches. Together, these findings enhance the interpretability of the results and broaden their analytical relevance beyond assessments based solely on descriptive frameworks.

4.3.1. Stage-Specific Responses and Key Driving Factors

The comprehensive evaluation results indicate that the effectiveness of coastal ecological restoration in Qingdao during 2010–2020 exhibited distinct stage-wise differences, and that these changes can be explained by the quantitative contribution structure of key indicators across different stages. During 2010–2015, the comprehensive score declined from 0.36 to 0.19, representing a decrease of 0.17, with hydrological pollution indicators exerting the most pronounced constraining effect on overall restoration effectiveness. During this period, declines in the standardized values of COD and ammonia nitrogen emissions (0.943 and 0.417, respectively) led to negative contributions of −0.0380 and −0.0204 to the comprehensive score, jointly explaining a substantial share of the observed decrease (Table 9). During the same period, the green coverage rate of built-up areas contributed −0.0499, further intensifying the stage-wise decline in overall restoration effectiveness. Restoration measures at this stage were predominantly characterized by localized and fragmented shoreline interventions, and had not yet evolved into a systematic framework for pollution control or spatial structure optimization.

Table 9. Contribution of Key Indicators.

First-Level Indicator	Secondary Indicator	Property	Entropy Weight	Standardized Change (2010–2015)	Contribution Change (2010–2015)	Standardized Change (2015–2020)	Contribution Change (2015–2020)
Hydrology	Total chemical oxygen demand (COD) emissions (tons)	Negative	0.0403	−0.943	−0.0380	+1.000	+0.0403
Hydrology	Total ammonia nitrogen (NH_3–N) emissions (tons)	Negative	0.0489	−0.417	−0.0204	+1.000	+0.0489
Vegetation	Bare land area	Negative	0.1091	0.000	0.0000	+1.000	+0.1091
Vegetation	Green coverage rate of built-up areas (%)	Positive	0.0499	−1.000	−0.0499	+0.396	+0.0197
Biology	Biodiversity	Positive	0.0447	+0.542	+0.0242	+0.458	+0.0205
—	Change in comprehensive score	—	—	—	−0.17	—	+0.55

From 2015 to 2020, the comprehensive score increased to 0.74, with a net rise of 0.55, reflecting a shift toward a phase of faster improvement in restoration outcomes. This change was mainly associated with the joint influence of spatial structure optimization and pollution control measures. Within this phase, the standardized value of bare land area increased by 1.000 and contributed +0.1091 to the comprehensive evaluation, representing the largest single contribution among all indicators. In parallel, substantial improvements in COD and ammonia nitrogen emissions generated positive contributions of +0.0403 and +0.0489 to the comprehensive score, respectively. Vegetation coverage and biodiversity indicators also exhibited sustained improvement, providing stable support for the overall restoration

effectiveness. These results indicate that, following the implementation of regional, system-oriented restoration projects such as the Blue Bay Initiative, high-weight indicators showed directionally consistent and pronounced improvements within the same stage, thereby quantitatively supporting the role of governance interventions in enhancing ecological restoration outcomes.

4.3.2. Heterogeneous Responses Across Multiple Dimensions

Different dimensions exhibited distinct response patterns over the study period. The Vegetation and Biology dimensions showed consistently positive trends and accounted for a substantial share of the overall score. This pattern suggests that ecological engineering measures, such as green space development and wetland restoration, are associated with changes in surface cover and habitat quality over time. In contrast, the Hydrology dimension exhibited higher sensitivity and variability, corresponding to temporal changes in pollutant emissions and governance intensity related to coastal environmental management. Within the Economy dimension, the V-shaped rebound in the proportion of fishery output value reflects concurrent changes in ecological conditions, resource-related indicators, and industrial structure over the study period. Climatic variations in hydrothermal conditions represent background environmental changes that coincided with observed trends in vegetation dynamics and ecosystem functioning.

4.3.3. Spatiotemporal Effects and Spatial Structural Changes

From a spatial perspective, the current-stage effectiveness of ecological restoration in the study area is primarily reflected in overall trends in spatial structural change, rather than in strictly quantified landscape optimization. Restoration projects have led to a substantial increase in total green coverage; however, the proportion of high-coverage areas has slightly declined, while medium–high coverage areas have continued to expand. This pattern indicates a gradual transition of urban green spaces from predominantly protective or ornamental functions toward more multifunctional ecological spaces. Under this process, vegetation distribution has shifted from a relatively concentrated, high-coverage pattern toward a more balanced and heterogeneous spatial arrangement, contributing to improved overall spatial continuity and system stability.

At the same time, a modest reduction in bare land has occurred alongside continued expansion of built-up land, highlighting the persistent constraints imposed by rapid urbanization on ecological restoration efforts. These results suggest that spatial structural improvements remain stage-dependent and conditional. Future restoration planning should therefore place greater emphasis on territorial spatial regulation and coordinated ecological space allocation to prevent restoration gains from being gradually offset by ongoing construction activities and increasing land-use intensity.

4.3.4. System-Oriented Thinking and a Long-Term Perspective in Ecological Restoration Projects

While existing restoration projects have produced observable short-term improvements, the full recovery of ecosystem structure and the stable delivery of ecosystem services remain processes that unfold over longer periods through natural succession. Accordingly, coastal ecological restoration requires a shift from a narrow emphasis on individual environmental indicators toward a more integrated and adaptive management approach that considers both immediate outcomes and long-term ecological security. Such an approach involves tailoring restoration strategies to local conditions, strengthening synergies between climate regulation and biodiversity conservation, and advancing an iterative process of evaluation, adjustment, and subsequent restoration. From a temporal perspective, the analytical design adopted in this study uses key governance stages as the units of analysis,

enabling the examination of stage-wise ecological responses within a long-term governance context. Comparisons based on representative years allow directional changes in restoration effectiveness and potential lag effects to be identified, while maintaining the comparability of multi-source indicators.

5. Conclusions

For coastal ecological restoration effectiveness, this study developed a dynamic evaluation framework, integrating multi-source remote sensing, InVEST, and the entropy-weighted TOPSIS method, and enable a multidimensional and long-term systematic assessment of restoration outcomes in the Qingdao coastal zone from 2010 to 2020. The main conclusions are summarized as follows:

(1) During the study period, the effectiveness of coastal ecological restoration in Qingdao exhibited a pronounced "V-shaped" evolutionary pattern. The comprehensive score declined from 0.36 in 2010 to 0.19 in 2015, before rebounding to 0.74 in 2020, representing an overall increase of 289% during the 2015–2020 period. This stage-wise change is temporally consistent with the intensified implementation of system-oriented ecological restoration programs, such as the Blue Bay Initiative, and the sustained strengthening of pollutant emission control after 2016, indicating that coordinated governance and integrated engineering interventions played a critical role in enhancing restoration effectiveness.

(2) Distinct differences were observed in the responses of indicators across different dimensions to restoration measures. The Biological + Vegetation Score exhibited a generally improving trend throughout the study period. Specifically, green coverage area increased from 19,203 ha in 2010 to 45,263 ha in 2020, while bare land area showed a continuous decline during 2015–2020. Meanwhile, the structural composition of habitat quality classes underwent adjustment, characterized by an increase in intermediate-quality areas and a contraction at both lower and higher ends of the quality spectrum; among these, the area classified as "moderate" quality increased by a net 404.35 km^2. By contrast, hydrological indicators showed a stage-wise deterioration during 2010–2015, with COD and ammonia nitrogen emissions increasing by 208.1% and 50.9%, respectively, which coincided with the decline in the comprehensive evaluation score, whereas the subsequent reduction in pollutant emissions after 2015 was associated with concurrent improvements in nearshore water quality and air quality.

(3) Based on the weight analysis, bare land area and annual maximum temperature were identified as key regulating factors in the comprehensive evaluation. Among these factors, bare land area, as a high-weight negative indicator, reflects a reduction in surface ecological exposure and the intensity of anthropogenic disturbance as it decreases, thereby underscoring the fundamental role of urban surface spatial management in ecological restoration. After removing climate-related variables, the temporal evolution of the comprehensive evaluation results remained consistent, indicating that the improvement in restoration effectiveness observed in 2020 was primarily attributable to the sustained implementation of human-driven restoration measures rather than to incidental climatic conditions.

(4) The proposed evaluation framework demonstrates clear methodological transferability and potential for regional adaptation. Built upon remote sensing data and publicly available statistical information, the framework supports dynamic, multidimensional assessment and provides a transferable evaluation tool for coastal cities and shoreline restoration projects; it helps overcome the limitations of traditional static, single-dimension evaluations and offers a scientific basis for temporal planning, indicator selection, and risk avoidance in ecological restoration planning.

This study develops a dynamic evaluation framework for coastal ecological restoration by integrating multi-source data and multi-dimensional indicators; however, certain limitations remain, leaving room for further extension in future research. First, to ensure temporal consistency among heterogeneous data sources, the analysis is conducted using representative key years and a stage-based comparison approach. Future studies could incorporate continuous time-series data or adopt quasi-experimental designs to enable a more rigorous examination of causal relationships between governance interventions and ecological responses. Second, the analysis of spatial structural change in this study is primarily based on macro-scale indicators such as land-use area and coverage. Future research could incorporate quantitative landscape pattern metrics to examine spatial configuration changes in greater detail, thereby providing deeper insights into the mechanisms underlying spatial structural evolution. In addition, although the indicator system covers key dimensions including vegetation, biological conditions, hydrology, economy, and climate, future studies could further quantify social governance processes and differences in project implementation, and integrate ecosystem process models with quasi-experimental research designs to conduct multi-scale and multi-regional comparative analyses. Such extensions would help strengthen the rigor of causal inference, deepen understanding of recovery mechanisms within coastal social–ecological systems, and provide more robust support for adaptive ecological restoration and spatial governance decision-making.

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Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

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

Appendix A

Table A1. Major ecological restoration projects in Qingdao.

Time	Project Name	Main Content
2010	Marine ranch construction	Artificial reef deployment and fish reproduction and release
2010	Tangdao Bay Wetland Park	Wetland vegetation restoration, ecological revetment construction, and water purification
2012	Daze Mountain Ecological Restoration	Afforestation, soil and water loss control, and ecotourism support
2012	Dagu River ecological restoration	River dredging, ecological bank protection, sewage interception network construction, and coastal vegetation restoration
2013	Licun River and Zhangcun River Management	Treatment of black and odorous water bodies, separation of rainwater and sewage, and construction of ecological wetlands
2013	Jiaozhou Bay Yuejin River Estuary Shoreline Improvement and Restoration Project	Bay beach and coastline improvement and restoration
2013	Lingshan Island Ecological Restoration Demonstration Project (Phase I)	The expansion and reconstruction of the Ring Island Road, domestic waste treatment, water storage and forestry, and bank protection projects
2013	Qingdao Polar Ocean World Partial Shoreline Renovation Project	Shoreline remediation and restoration

Table A1. *Cont.*

Time	Project Name	Main Content
2013	Qingdao Taipingjiao partial shoreline improvement project	Shoreline cleanup and improvement
2014	Qingdao Laoshan Road No. 2 Shoreline Improvement Project	Damaged coastline remediation and restoration
2014	Qingdao Xiaogangwan Shoreline Improvement and Restoration Project	Shoreline renovation and restoration in severely damaged areas
2014	Comprehensive Management of Moshui River	River channel widening, dredging and sewage interception, and waterfront landscape belt construction
2016	Lingshan Bay Coastal Restoration	Beach restoration, seawall ecological transformation, and coastal vegetation planting
2016	Comprehensive improvement project of part of the shoreline of Jiaozhou Bay in the lower reaches of Baisha River in Chengyang District	Seawall greening and renovation project and tide dam construction
2016	Qingdao Dagong Island Protection and Development Demonstration Project	Wharf construction and upgrading, road construction and maintenance, sewage treatment projects, and ecological environment monitoring station construction
2016	2016 Qingdao Blue Bay Renovation Project—Comprehensive Coastline Renovation Project in the Hongshiya Section and the Hanbilou to Jinshatan Section of Jiaozhou Bay in the West Coast New Area	Shoreline regulation and restoration
2019	2019 Blue Bay Remediation Project—Xiaodao Bay North Shore Coastal Zone Comprehensive Remediation Project, Xiaoguan Island Ecological Restoration Project	Coastline regulation, shoreline restoration, seaward river regulation, damaged vegetation restoration and other projects
2019	Zhaitang Island Ecological Protection and Restoration Project (Phase I)	Cleaning and demolition of aquaculture ponds around the islands, and construction of island revetment projects

Table A2. Raw data and normalized results.

	Raw Data			Normalized Matrix		
Year	**2010**	**2015**	**2020**	**2010**	**2015**	**2020**
Bare land area	0.0004	0.0004	0.0002	0	0	1
Vegetation coverage	0.9908	0.99	0.9867	1	0.80487805	0
Green coverage area (hectares)	19,203	30,201	45,263	0	0.42202609	1
Green coverage rate of built-up areas (%)	43.38	39.44	41	1	0	0.395939
Biodiversity	0.955357361	0.964414	0.972078	0	0.54164659	1
Proportion of fishery output value (%)	0.21756553	0.197025	0.239553	0.482982	0	1
Port cargo throughput (10,000 tons)	35,012	49,749	60,459	0	0.57912524	1
Air quality good rate (%)	90.7	80.3	86.3	1	0	0.576923
Proportion of nearshore waters meeting quality standards (%)	87.5	84.4	98.8	0.215278	0	1
Total sulfur dioxide (SO_2) emissions (tons)	112,762.72	91,119	4830.65	0	0.20053095	1
Total chemical oxygen demand COD emissions (tons)	46,633.56	143,690.5	40,793.42	0.943243	0	1
Total ammonia nitrogen (NH_3-N) emissions (tons)	8076.13	12,193.35	2312.66	0.416694	0	1
Mean annual temperature (°C)	12.8	13.7	13.9	1	0.18181818	0
Annual precipitation (mm)	713.9	421.2	1093.8	0.435177	0	1
Annual maximum temperature (°C)	34.8	34.8	32	0	0	1
Annual minimum temperature (°C)	−11.1	−6.5	−11.2	0.978723	0	1
Sunshine duration (hours/year)	2096	2117.9	2620	0	0.04179389	1

Table A3. Closeness for each year.

	ALL			Biological + Vegetation			No Climate		
Year	**D+**	**D−**	**Si**	**D+**	**D−**	**Si**	**D+**	**D−**	**Si**
2010	0.2175	0.1226	0.3605	0.3636	0.2649	0.4215	0.2512	0.1443	0.3648
2015	0.2394	0.0553	0.1876	0.2021	0.1711	0.4586	0.2721	0.0836	0.235
2020	0.0857	0.2405	0.7374	0.4328	0.3906	0.4743	0.084	0.2842	0.772

References

1. Gao, J.; An, T.; Zhang, K.; Zhao, R. Development and reform of marine spatial planning in China under the new territorial spatial planning system. *Mar. Dev.* **2024**, *2*, 2. [CrossRef]
2. Lotze, H.K.; Lenihan, H.S.; Bourque, B.J.; Bradbury, R.H.; Cooke, R.G.; Kay, M.C.; Kidwell, S.M.; Kirby, M.X.; Peterson, C.H.; Jackson, J.B.C. Depletion, Degradation, and Recovery Potential of Estuaries and Coastal Seas. *Science* **2006**, *312*, 1806–1809. [CrossRef]
3. Lu, G.; Pang, X.; Hou, J.; Hao, J. Evaluation and prediction of ecological security in Shizuishan City based on PSR model. *J. Saf. Environ.* **2023**, *23*, 3784–3792. [CrossRef]
4. Du, H.; Wang, J.; Wang, J.; Ma, Y. Research progress on evaluation of ecological restoration effectiveness based on ecosystem characteristics. *Geol. Bull. China* **2025**, *8*, 1371–1384. Available online: https://www.cgsjournals.com/dztb/article/doi/10.12097/gbc.2024.10.029 (accessed on 27 January 2026). [CrossRef]
5. Zhang, Q.; Bai, J.; Ma, Y.; Gao, W.; Tu, J. Research on the method for evaluating ecological restortaion effect in the coastal zone of Tianjin. *Mar. Environ. Sci.* **2019**, *38*, 782–789+795.
6. Yu, X.; Yu, J. Policy development, current problems and recommendations for coastal ecological restoration in China. *Chin. Fish. Econ.* **2020**, *38*, 8–16. Available online: https://d.wanfangdata.com.cn/periodical/CiBQZXJpb2RpY2FsQ0hJU29scjkyMDI2MDExMjE3MDQyNhIPemd5eWpqMjAyMDA1MDAyGghlc2dzd2hlNw== (accessed on 27 January 2026). [CrossRef]
7. Danovaro, R.; Aronson, J.; Bianchelli, S.; Boström, C.; Chen, W.; Cimino, R.; Corinaldesi, C.; Cortina-Segarra, J.; D'Ambrosio, P.; Gambi, C.; et al. Assessing the success of marine ecosystem restoration using meta-analysis. *Nat. Commun.* **2025**, *16*, 3062. [CrossRef]
8. Liu, J.; Du, J.; Zhang, C.; Zhang, J.; Yang, H.; Donald, M.L.; Wu, Y.; Dong, T. Ecosystem service assessment under ecological restoration programs: A systematic review of studies from China. *Front. Ecol. Evol.* **2023**, *11*, 1152907. [CrossRef]
9. Liu, C.; Tan, S.; Jiao, W. Methods and applications for assessing the implementation effectiveness of ecological restoration planning in national land space. *J. Nat. Resour.* **2024**, *39*, 2484–2496. [CrossRef]
10. Wu, S.; Lai, J. Current Situation of Wetland Ecological Protection and Ecological Restoration Models under the Background of Territorial Spatial Planning. *Environ. Sci. Manag.* **2024**, *49*, 164–168. Available online: https://d.wanfangdata.com.cn/periodical/CiBQZXJpb2RpY2FsQ0hJU29scjkyMDI2MDExMjE3MDQyNhINYmZoajIwMjQxMDAzNhoIeGl3ODZidjY= (accessed on 27 January 2026). (In Chinese) [CrossRef]
11. Sarker, J.R.; Rolfe, J.; Ananda, J. Analysis of technical efficiency of dry season rice production in saline and non-saline areas of Bangladesh. *J. Environ. Manag.* **2022**, *316*, 115256. [CrossRef]
12. Dou, X.; Li, W.; He, Y.; Zhao, Y.; Sang, Q.; Wang, Y.; Wang, C.; Yan, Y. Assessing the future effectiveness of ecological protection and restoration by compiling ecological patterns & services indicators and multi-scenario simulation. *Environ. Sustain. Indic.* **2025**, *28*, 100939. [CrossRef]
13. Li, X. TOPSIS model with entropy weight for eco geological environmental carrying capacity assessment. *Microprocess. Microsyst.* **2021**, *82*, 103805. [CrossRef]
14. Xu, X.; Zhang, Z.; Long, T.; Sun, S.; Gao, J. Mega-city region sustainability assessment and obstacles identification with GIS–entropy–TOPSIS model: A case in Yangtze River Delta urban agglomeration, China. *J. Clean. Prod.* **2021**, *294*, 126147. [CrossRef]
15. Du, Y.-W.; Gao, K. Ecological security evaluation of marine ranching with AHP-entropy-based TOPSIS: A case study of Yantai, China. *Mar. Policy* **2020**, *122*, 104223. [CrossRef]
16. Zhang, L.; Zhang, M.; Guo, Y. Entropy-Weighted TOPSIS-Based Ecological Environment Driving Factors in the Chaohu Lake Rim Region Temporal and Spatial Differentiation Study. *Pol. J. Environ. Stud.* **2024**, *33*, 5459–5471. [CrossRef] [PubMed]
17. Zhang, L.; Zhang, X.; Yuan, S.; Wang, K. Economic, Social, and Ecological Impact Evaluation of Traffic Network in Beijing–Tianjin–Hebei Urban Agglomeration Based on the Entropy Weight TOPSIS Method. *Sustainability* **2021**, *13*, 1862. [CrossRef]
18. Wang, M.; Wang, X.; Zhou, R.; Zhang, Z. An indicator framework to evaluate the Blue Bay Remediation Project in China. *Reg. Stud. Mar. Sci.* **2020**, *38*, 101349. [CrossRef]
19. Liu, L.; Lin, B.; Fang, Q.; Jiang, X. Effectiveness assessment of China's coastal wetland ecological restoration: A meta-analysis. *Sci. Total Environ.* **2024**, *934*, 173336. [CrossRef]
20. Lu, W.; Xu, C.; Wu, J.; Cheng, S. Ecological effect assessment based on the DPSIR model of a polluted urban river during restoration: A case study of the Nanfei River, China. *Ecol. Indic.* **2019**, *96*, 146–152. [CrossRef]

21. Li, X.; Ji, B.; Li, N.; Chen, Q.; Anderson, C.J.; Wang, Y. Assessing the Effectiveness of Large-Scale Ecological Restoration Measures in the Liaohe Estuary Using a Landscape Pattern Perspective. *Sustainability* **2024**, *16*, 7151. [CrossRef]
22. Pang, B.; Yang, W.; Cui, B.; Zhang, S.; Xie, T.; Ning, Z.; Gao, F.; Zhang, H. Evaluation of the effect of vegetation restoration in The Yellow River delta wetland biodiversity conservation project. *Environ. Eng.* **2023**, *41*, 213–221. Available online: https://d.wanfangdata.com.cn/periodical/CiBQZXJpb2RpY2FsQ0hJU29scjkyMDI2MDExMjE3MDQyNhINaGpnYzIwMjMwMTAyNxoIZmZzZXI1ZW8= (accessed on 27 January 2026). [CrossRef]
23. Wang, W.; Xu, C.; Sun, J. Study on evaluation index system of the effect of ecological transformation and restoration in the artificial coasts. *Coast. Eng.* **2020**, *39*, 70–76.
24. Wu, S.; Liu, L. The Comprehensive Evaluation Index System of Island Ecological Restoration Effect. *Ocean Dev. Manag.* **2023**, *40*, 97–102.
25. Lin, X.; Li, C.; Jiang, D.; Liu, J.; Huang, B.; Wu, J. Construction and Preliminary Application Reasearch of Blue Bay Index Evaluation System: Taking Dongtou district of Wenzhou city as an example. *Ocean Dev. Manag.* **2020**, *37*, 46–51.
26. Bersoza Hernández, A.; Brumbaugh, R.D.; Frederick, P.; Grizzle, R.; Luckenbach, M.W.; Peterson, C.H.; Angelini, C. Restoring the eastern oyster: How much progress has been made in 53 years? *Front. Ecol. Environ.* **2018**, *16*, 463–471. [CrossRef]
27. Gómez-Baggethun, E.; Tudor, M.; Doroftei, M.; Covaliov, S.; Năstase, A.; Onără, D.-F.; Mierlă, M.; Marinov, M.; Doroșencu, A.-C.; Lupu, G.; et al. Changes in ecosystem services from wetland loss and restoration: An ecosystem assessment of the Danube Delta (1960–2010). *Ecosyst. Serv.* **2019**, *39*, 100965. [CrossRef]
28. McCormick, A.; Fisher, K.; Brierley, G. Quantitative assessment of the relationships among ecological, morphological and aesthetic values in a river rehabilitation initiative. *J. Environ. Manag.* **2015**, *153*, 60–67. [CrossRef] [PubMed]
29. Westling, E.L.; Surridge, B.W.J.; Sharp, L.; Lerner, D.N. Making sense of landscape change: Long-term perceptions among local residents following river restoration. *J. Hydrol.* **2014**, *519*, 2613–2623. [CrossRef]
30. Gao, J.; Shi, Y.; Zhang, H.; Chen, X.; Zhang, W.; Shen, W.; Xiao, T.; Zhang, Y. China Regional 250m Fractional Vegetation Cover Data Set (2000–2024). 2022. Available online: https://data.tpdc.ac.cn/zh-hans/data/f3bae344-9d4b-4df6-82a0-81499c0f90f7 (accessed on 1 February 2026).
31. Yang, J.; Huang, X. The 30 m annual land cover datasets and its dynamics in China from 1990 to 2020 (1.0.0). *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. [CrossRef]
32. Xia, Z.; Liu, L.; Yuan, C.; Wei, X.; Huang, J.; Wang, Y. Assessment and zoning of habitat services in urban fringe areas from the perspective of social-ecological coupling. *Acta Ecol. Sin.* **2024**, *44*, 1501–1513. [CrossRef]
33. Yan, L.; Cao, G.; Kang, L.; Liu, M.; Ye, D. Analysis of spatial and temporal changes in habitat quality and driving factors in Gonghe County using the InVEST model. *Arid. Zone Res.* **2024**, *41*, 314–325. [CrossRef]
34. Chen, M.; Huang, R. Evaluation of habitat quality in Chengdu City Based on InVEST Model. *J. Sichuan For. Sci. Technol.* **2025**, *46*, 84–90.
35. Zhang, J.; Zhao, R.; Lei, J. Spatio-temporal evolution of habitat quality in Haikou from 2000 to 2020 based on InVEST model. *J. Zhejiang AF Univ.* **2025**, *42*, 383–392.
36. Zhao, Q.; Wang, T.; Wang, T.; Cheng, S. InVEST model-based analysis of spatiotemporal evolution characteristics of habitat quality in the ecological green integrated demonstration area, Yangtze River Delta. *Remote Sens. Nat. Resour.* **2024**, *36*, 187–195.
37. Liu, X.; Li, S.; He, H.; Qin, H.; Wang, S.; Sun, X. Analysis of Land Use Change and Habitat Quality Evolution Based on InVEST and PLUS Models: Example from Hanzhong Basin. *Northwestern Geol.* **2024**, *57*, 271–284.
38. Sharp, R.; Chaplin-Kramer, R.; Wood, S.; Guerry, A.; Tails, H.; Ricketts, T. *InVEST User's Guide*; The Natural Capital Project: San Francisco, CA, USA, 2018.
39. Li, F.; Liu, Q.; Jiao, Z. Remote Sensing Dynamic Monitoring of Vegetation Coverage in Jiulianshan Nature Reserve, Jiangxi Province. *For. Prospect Des.* **2015**, *2015*, 63−68+75. Available online: https://d.wanfangdata.com.cn/periodical/CiBQZXJpb2RpY2FsQ0hJU29scjkyMDI2MDExMjE3MDQyNhIRbGlueWtjc2oyMDE1MDEwMTYaCHh1bHU0dDJr (accessed on 27 January 2026). (In Chinese)
40. Chen, S.; Wang, X.; Qiang, Y.; Lin, Q. Spatial–temporal evolution and land use transition of rural settlements in mountainous counties. *Environ. Sci. Eur.* **2024**, *36*, 38. [CrossRef]
41. Zhao, D.-Y.; Ma, Y.-Y.; Lin, H.-L. Using the Entropy and TOPSIS Models to Evaluate Sustainable Development of Islands: A Case in China. *Sustainability* **2022**, *14*, 3707. [CrossRef]
42. Shandong Administration for Market Regulation. Guidelines for Comprehensive Benefit Evaluation of Marine Ecological Restoration. 2024. Available online: https://std.samr.gov.cn/db/search/stdDBDetailed?id=21E6D7791CB78328E06397BE0A0AE3FC (accessed on 27 January 2026).
43. Palmer, M.A.; Bernhardt, E.S.; Allan, J.D.; Lake, P.S.; Alexander, G.; Brooks, S.S.; Carr, J.; Clayton, S.; Dahm, C.N.; Follstad Shah, J.J.; et al. Standards for ecologically successful river restoration. *J. Appl. Ecol.* **2005**, *42*, 208–217. [CrossRef]
44. Priya, U.K.; Senthil, R. Framework for Enhancing Urban Living Through Sustainable Plant Selection in Residential Green Spaces. *Urban Sci.* **2024**, *8*, 235. [CrossRef]

45. Zhang, X.; Jin, X. Vegetation dynamics and responses to climate change and anthropogenic activities in the Three-River Headwaters Region, China. *Ecol. Indic.* **2021**, *131*, 108223. [CrossRef]
46. Xie, J.; Zhou, S.; Chung, L.C.H.; Chan, T.O. Evaluating land-surface warming and cooling environments across urban–rural local climate zone gradients in subtropical megacities. *Build. Environ.* **2024**, *251*, 111232. [CrossRef]
47. Shi, Y.; Jin, N.; Ma, X.; Wu, B.; He, Q.; Yue, C.; Yu, Q. Attribution of climate and human activities to vegetation change in China using machine learning techniques. *Agric. For. Meteorol.* **2020**, *294*, 108146. [CrossRef]
48. Bugnot, A.B.; Gorman, D.; Steven, A.D.L.; Vanderklift, M.A. Measuring fisheries outcomes from coastal wetland restoration: A review and meta-analysis. *Restor. Ecol.* **2025**, *33*, e14324. [CrossRef]
49. Campello, B.S.C.; Duarte, L.T.; Romano, J.M.T. Dealing with multi-criteria decision analysis in time-evolving approach using a probabilistic prediction method. *Eng. Appl. Artif. Intell.* **2022**, *116*, 105462. [CrossRef]

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