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Measurement of Coastal Marine Disaster Resilience and Key Factors with a Random Forest Model: The Perspective of China's Global Maritime Capital

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Abstract: Frequent outbreaks of marine disasters in the context of global warming pose a serious threat to the sustainable development of coastal areas and the construction of global maritime capitals. Implementing integrated marine and coastal management and assessing and enhancing cities' resilience to marine disasters are of practical importance. Based on the capital perspective, this study innovatively constructed a framework for the Coastal Marine Disaster Resilience Index (CMDRI) for the coastal city level, considering the main marine disaster characteristics of Chinese coastal areas. Eight coastal cities in China proposed to build global maritime capitals were used as research objects. The random forest model, which can handle complex nonlinear systems and feature importance, was applied for the first time to resilience assessment and key factor identification in marine disasters. The results show that the overall level of CMDRI of each city is steadily increasing, with Shenzhen having the highest marine disaster resilience grade for each year and Zhoushan having the lowest. Economic and human capitals accounted for a more significant proportion of key factors, followed by physical and social capitals, and environmental capital accounted for a minor proportion. The comparison results of model performance show that the random forest model has better fitting accuracy and stability in assessing CMDRI and can be further applied to other disaster resilience and sustainability areas.

Keywords: sustainable development; ocean and coastal management; machine learning; marine disaster resilience evaluation; feature importance

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1. Introduction

The Sustainable Development Goals (SDGs) adopted by the United Nations in 2015 set forth a basis to pursue the sustainable development of coastal cities that have long been an important gathering place for the global population and economic growth [1]. As coastal areas are becoming increasingly dependent on ocean resources, leading ocean core competencies, and playing an essential role in a certain region [2], the creation of global maritime capital has significant implications for the sustainable development of coastal areas. In 2017, China proposed to build global maritime capitals in cities such as Shenzhen and Shanghai. Subsequently, eight cities in China have successively put forward the vision of building and developing global maritime capitals, including two municipalities (Shanghai and Tianjin), one provincial capital (Guangzhou), four sub-provincial cities (Shenzhen, Dalian, Qingdao, Ningbo) and one prefecture-level city (Zhoushan).

However, coastal cities are at a higher risk of being affected by marine disasters such as storm surges, red tides and waves than other cities [3]. Under global warming, the interaction imbalance between the atmosphere and the ocean represented by ENSO (El Nino and Southern Oscillation) occurs frequently, and the intensity and frequency of marine disasters are further enhanced. It seriously limits the sustainable development of maritime finance and trade, the governance of the maritime industry and marine culture in coastal cities. Therefore, the construction of a global maritime capital must take into account the management of maritime catastrophes. Vulnerability refers to the propensity to be adversely affected and encompasses a variety of indexes including adaptive capacity, sensitivity and exposure [4]. Vulnerability assessment is an important component of disaster risk management and an effective tool to formulate policies and guide priority disaster reduction measures [5,6]. However, recent research has started to shift from disaster vulnerability to resilience, as resilience is recognized as an optimistic and practical expression of engagement in emergencies [7–9]. The importance of research on disaster resilience has been recognized by international organizations and cooperation treaties. In 2010, the United Nations Office for Disaster Risk Reduction (UNDRR) launched the "Cities are Resilient" campaign to encourage cities to join in building resilience [10]. In addition, the Sendai Framework for Disaster Risk Reduction 2015–2030 emphasized the restoration capacity of disasters through the implementation of inclusive and integrated social, economic, institutional, technological, educational and political measures [11]. The SDGs also emphasized building community resilience to natural disasters, with a focus on local planning and management [12].

Many conceptual frameworks have been proposed for the assessment of disaster resilience. Mayunga proposed a capital-based approach and constructed a conceptual framework of Community Disaster Resilience Index (DRI) that includes social, economic, demographic, material and natural capitals [13]; Cutter et al. argued that disaster resilience has multiple dimensions, including physical, social, institutional, economic, and ecological factors, and proposed a Baseline Resilience Indicator for Communities (BRIC) based on the theoretical framework of the Disaster Resilience of Place (DROP) model [7,8]; Joerin et al. assessed the physical, social and economic resilience of individuals through a Climate-related Disaster Community Resilience Framework (CDCRF) [14]; Yoon et al. proposed the Community Disaster Resilience Index (CDRI), measured by human, social, economic, environmental, and institutional factors, for the comprehensive disaster resilience of the entire country of South Korea [15]; Lam et al. and Cai et al. proposed the Resilience Inference Measurement (RIM) model to assess and validate community resilience to coastal hazard in the Caribbean and Mississippi regions [16,17]. In addition, scholars have conducted several studies on different types of hazards, such as multiple hazards [18–21], hurricanes [22], floods [4,23,24] and earthquakes [25]. However, a unified framework and model for disaster resilience assessment is still lacking [9]. A widely adopted resilience model is based on the capital division model to divide the study unit's resilience, according to different components such as demographic, economic, social, and material capitals, which are necessary to develop a sustainable economy [13]. The more capital the research unit has, the more resilient it is, which emphasizes the research unit's capacity and its stakeholders' ability to adapt. A capital perspective can provide policy makers with a clearer picture of resilience actions and strategies [21].

Current assessment methods for disaster resilience mainly include tool evaluation models, scorecard models and indicator evaluation models [26–28]. Compared to the previous two approaches, indicator-based evaluation can summarize complex or multifaceted problems into a simple form that is easy to understand [9,15] and help to compare longitudinal or transverse results [7]. Since disaster resilience is an abstract, multidimensional and interdisciplinary concept [15], the indicator evaluation model is more commonly used in this research area [7,13]. However, as a complex nonlinear system at the intersection of nature and socio-economics, disaster resilience assessments based on the indicator system approach continue to be controversial in terms of quantification and assessment methods. The controversial portion mainly involves determining subjective or objective weights and aggregation techniques for compensatory or non-compensatory resilience indices [27,28].

In addition, there are fewer articles on the identification of the key influencing factors of disaster resilience. Some references have used regression methods to identify key factors affecting disaster resilience [15,17,22]. However, as a comprehensive problem, the large number of influencing factors involved in disaster resilience is prone to have the curse of dimensionality, and problems such as multiple co-linearities in the regression process are difficult to solve. Machine learning, on the other hand, has inherent advantages in overcoming the curse of dimensionality and nonlinear problems through information mining and is also outstanding in assessment accuracy. Among them, random forest (RF), as an integrated learning method, is insensible to multicollinearity and is not susceptible to overfitting. It has a fast-learning process, does not require normalization of variable units, and has good tolerance for aberrations and noises [29,30]. It is also possible to identify critical indicators of the fitted results based on the RF model, which is beneficial for subsequent improvement work [31]. Researchers have attempted to apply RF to flood disasters and have achieved good assessment results [32]. However, to the best of our knowledge, the use of RF models in marine disaster resilience is very limited.

Based on this, our study constructed and measured the Chinese Coastal Marine Disaster Resilience Index (CMDRI), and then applied the RF model to assess marine disaster resilience and identified the key influencing factors of CMDRI for eight coastal cities in China that are proposed to build a global maritime capital. Finally, multiple evaluation indicators such as MAE, MAPE, R^2, RMSE and a five-fold cross-validation were used to compare and validate the reasonableness and reliability of the RF assessment results. The contributions of this study arethe following: firstly, the innovative construction and measurement of the CMDRI for Chinese coastal cities complements and expands the research content in the field of disaster resilience, taking into account the characteristics of major marine disasters suffered by Chinese coastal cities; secondly, we applied the RF model for the first time to the evaluation of marine disaster resilience and the identification of key factors, which solves previous problems such as ambiguity in assessing complex nonlinear systems and the curse of dimensionality, and has significant academic value.

This paper is divided into five parts. Section 1 is the introduction and Section 2 depicts the construction of CMDRI and data sources. Section 3 describes the research methods used in this paper. Details on the main empirical results and discussions are conducted in Section 4. The last section is the conclusion and future research needs.

2. Construction of Coastal Marine Disaster Resilience Index (CMDRI) and Data Sources

The term "resilience" is often used in the same way as the concept of "bouncing back" that reflects its Latin root, "resiliere" [33]. The concept of resilience was introduced into ecology by Holling in 1973 to describe the behavior of dynamic systems that stay stable despite disturbances and changes [34]. Subsequently, Timmerman in 1981 introduced the concept of resilience into the field of natural disasters, defining it as the ability of a system to absorb disaster disturbances and recover from disaster events [35]. Since then, the study of disaster resilience has been valued by scholars and experts in the fields of socio-economics, environmental change and disaster [36]. The definition of resilience varies depending on the goals of the study. The UNDRR and National Research Council (NRC) defined it as the ability of a system, community or society exposed to hazards to resist, absorb, accommodate and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions [37,38]. This definition has been identified as the most appropriate definition for resilience [39]. Cutter et al. defined resilience as the ability of individuals or communities to adapt through resistance or change to achieve and sustain their survival and functioning, and the social aspect less formally involves the ability of individuals to recover with minimal disruption [7]. Mayunga proposed a capital-based approach and viewed resilience as the ability of communities and their built environment to quickly mitigate, prepare, respond to and recover from disasters and adapt to new situations while learning from past disasters [13]. Lam et al. defined resilience by including both aspects of vulnerability to hazards and adaptive capacity over time. In their view, resilience is the ability to successfully prepare, plan, absorb, recover from, and adapt to adverse events [16].

Although many researchers have given the definition of disaster resilience, there is still a lack of consensus on the selection of disaster resilience indicators. The main reason behind this is the different nature of socio-economic systems and organizational environments of research units [7]. However, these indicators can be converted from one region to another based on data availability and understanding [9]. With reference to the existing literature, this study defines coastal marine disaster resilience as "the ability of coastal cities to rapidly mitigate, prepare, respond and recover from, and adapt to new disaster situations while learning from past marine disasters". Based on the capital perspective, human, social, economic, physical and environmental capitals were selected [8,15,22,36,37,40] to construct the framework of Coastal Marine Disaster Resilience Index (CMDRI), as shown in Figure 1. Combined with the characteristics of marine disasters in coastal cities and data availability, 34 capacity indicators and 18 sub-dimensions were selected, covering five capitals of disaster resilience (Table 1). The existing literature also contains indicators of other dimensions, such as cultural indicators (organizational beliefs, religions, etc.). However, considering the coastal city scale and the data unavailability, they were not included in this study [28].

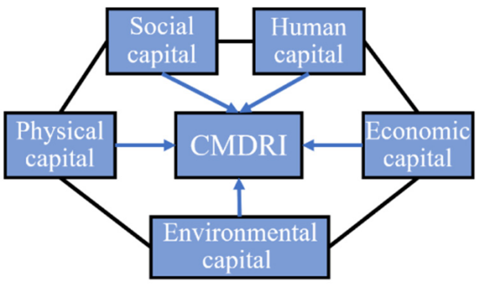

Figure 1. Conceptual framework for Coastal Marine Disaster Resilience Index (CMDRI) in China.

Table 1. Dimensions and indicators of coastal marine disaster resilience.

Dimensions	Sub-Dimensions	Indicators	Effect on CMDRI
Human capital (A)	Demographics (A1)	Population density (person/km^2) (A11)	Positive
		Average population per household (person) (A12)	Positive
		Population burdened by each employed person (person) (A13)	Negative
	Gender structure (A2)	Sex ratio of population (%) (A21) [1]	Positive
	Age structure (A3)	Percent of population aged 0-14 (%) (A31)	Negative
		Percent of population over 65 (%) (A32)	Negative
	Educational attainment (A4)	Percent of population with high school education and above (%) (A41)	Positive
Social capital (B)	Information transportation (B1)	The ratio of telephone users (10,000 households/10,000 persons) (B11)	Positive
		Number of civilian vehicles per 10,000 persons (vehicle) (B12)	Positive
	Social assistance (B2)	Number of health facilities per 10,000 persons (unit) (B21)	Positive
		Number of technicians in health facilities per 10,000 persons (person) (B22)	Positive
		Number of beds in health facilities per 10,000 persons (bed) (B23)	Positive

Table 1. *Cont.*

Dimensions	Sub-Dimensions	Indicators	Effect on CMDRI
Economic capital (C)	Economy level (C1)	GDP per capita (CNY) (C11)	Positive
		Gross Regional Product (100 million CNY) (C12)	Positive
		Disposable income per capita (CNY) (C13)	Positive
		General public budget revenue (100 million CNY) (C14)	Positive
	Investment level (C2)	Total fixed asset investment (10,000 CNY) (C21)	Positive
	Economy diversity (C3)	Percentage of non-vulnerable industries value (%) (C31)	Positive
	Employment level (C4)	Registered urban unemployment rate (%) (C41)	Positive
	Foreign trade (C5)	Total import and export value (100 billion USD) (C51)	Positive
Physical capital (D)	Basic physical capital (D1)	Drainage pipe density (km/km^2) (D11)	Positive
		Road length per capita (km/10,000 persons) (D12)	Positive
	Critical physical capital (D2)	Total water supply per capita (10,000 m^3/10,000 persons) (D21)	Positive
		Total electricity consumption per capita (10,000 kWh/10,000 persons) (D22)	Positive
	Housing conditions (D3)	Area of residential building per capita (m^2) (D31)	Positive
	Temporary shelter service (D4)	Number of temporary shelters (unit) (D41)	Positive
Environmental capital (E)	Natural resources (E1)	Area of green park per capita (m^2) (E11)	Positive
		Coverage rate of urban green area (%) (E12)	Positive
	Disaster causing factors (E2)	Industrial wastewater discharge per unit industrial value (10,000 CNY/10,000 tons) (E21)	Negative
		Sewage treatment capacity of sewage treatment plants (10,000 tons/day) (E22)	Positive
		Rainfall (mm) (E23)	Negative
		Height of sea level rise relative to normal years (mm) (E24)	Negative
	Geographical conditions (E3)	Percentage of urban elevation below 5m area (%) (E31)	Negative
		Coastline length (km) (E32)	Negative

Note: [1] Female = 100%.

Human capital refers to the innate, derived or accumulated capacity of human beings to cooperate effectively with other forms of capital to sustain all aspects of economic production and life during all phases of a disaster [41]. This study uses four components to measure the characteristics associated with disaster phases: demographics, gender structure, age structure, and educational attainment. Social capital is defined primarily as the social structures and networks that promote collective action [36], with a general emphasis on coordination and cooperation in the mutual interest. This study of social capital refers to the characteristics of information, communication and the capacity of social assistance organizations, mainly to improve resilience during disasters and in post-disaster reconstruction [15]. Economic capital is commonly defined as the financial resources that people use to support themselves [36]. It comprises principally the level and diversity of the economy, the level of investment, employment and foreign trade. Among them, economic diversity means that the urban economy should not rely on the development of a single industry that is more affected by the marine disaster. Otherwise, it is difficult to quickly recover from the final stages of the catastrophe. This study reflects the proportion of other industries that have eliminated industries that are easily impacted by marine disasters, such as transportation, accommodation and tourism [8]. Economic capital measures the ability of cities to withstand financial disruptions caused by damage and losses from marine disasters. Cities with more robust economic and financial resources have greater resilience.

In this study, physical capital is defined as the overall built environment [36] that helps people sustain their livelihoods, including basic physical capital, critical physical capital, housing conditions for residents, and the number of schools, libraries, and hotel establishments that can provide temporary shelter services in a disaster event. Physical capital is critical to the effective functioning of cities, especially during evacuations, to ensure that people have the resources and support they need in an emergency. Environmental characteristics in terms of resources and atmospheric and geographic factors are also considered in measuring resilience to marine hazards [32]. Environmental capital is essential for the maintenance of all life forms, including human life [41]. Storm surges, red tides, and waves are the major marine hazards experienced in China's coastal areas. Therefore, this study innovatively included the disaster-causing factors and geographic conditions that lead to the major marine hazards to the environmental capital, such as wastewater discharge, rainfall, sea level height elevations and coastal line data. In addition, natural resources such as green area cover were also included to measure the impact of urban hazard mitigation.

The data in this paper came from the statistical yearbooks, the national economic and social development bulletins of eight coastal cities, the China Marine Disaster Bulletin, the China Sea Level Bulletin, and the China Economic and Social Development Statistical Database. The indicators reflecting the age structure and education attainment do not have annual data. This paper linearly interpolated according to the results of each city's fifth, sixth and seventh population census bulletins. The urban elevation data were obtained from the China geographic information resource catalog service system (http://www.webmap.cn/ (accessed on 20 August 2022)), based on ArcGIS software (Release 10.7, Environmental Systems Research Institute, Redlands, CA, USA) for unified processing after spatial statistics. Some data were calculated based on statistical data, and the missing data were supplemented with the mean value method.

3. Methods

3.1. Random Forest

This study evaluated CMDRI and identified key factors in eight coastal cities of China based on random forest (RF). RF is an integrated learning method based on decision trees constructed from a classification and regression tree (CART) algorithm, and has been widely used for classification problems, regression problems, and variable importance problems [42]. The basic idea is: based on Bootstrap, N training sample sets are independently drawn from the original training set for a total of n times. In this process, n decision tree models are built for each newly created n training sample set, and n results are obtained. The final results are determined based on the n results voting. As an integrated learning method, RF randomly draws sample data from the training set with put-back to form a self-help training set, while the process of constructing a decision tree randomly selects feature variables as splitting attributes. Thus, RF is insensitive to aberrations and noises, overcoming the problem of overfitting [43]. During Bootstrap sampling, the probability that each sample is not drawn $P_i = (1 - 1/N)^N$. When N is large enough, $(1 - 1/N)^N$ will converge to $1/e \approx 0.368$, indicating that about 37% of the samples in the original sample set will not appear in the Bootstrap sample, and these data are also called Out of Bag (OOB) data. OOB data are equivalent to a built-in cross-validation process that improves the generalization ability of the RF model. Considering that OOB data can obtain unbiased estimates of the computed generalization error [42], this study used the OOB error calculated based on Root Mean Squared Error (RMSE) as one of the model accuracy indicators. Given that Gini importance measure variable importance is biased [44], this study used RF-based permutation importance for the identification of key factors. The permutation variable importance of each indicator is the increase in the Mean Squared Error (MSE) in the model when the particular variable is permuted. The association between the predictor and the target is destroyed by randomly shuffling the observations of the particular variable. This method will randomly shuffle each feature and compute the change in the model's performance. The features which affect the performance the most are the most important. The advantage of the permutation importance based on RF is that it covers the impact of each predictor variable individually as well as multivariate interactions with other predictor variables [44].

The operation mode determines that the RF model has strong data mining ability and extremely high prediction accuracy. It is insensitive to multicollinearity and is not prone to overfitting, and has inherent advantages in overcoming problems such as the curse of dimensionality and nonlinear systems [29,30]. The permutation importance based on RF, especially, can integrate the relationship between variables and other variables to identify key factors. Given that coastal marine disaster resilience is a comprehensive concept covering human, social, economic, physical and environmental capitals, this study applied the RF model to marine disaster resilience assessment for the identification of key factors for the first time. It can solve the problems of the ambiguity of complex nonlinear systems and curse of dimensionality in assessing the resilience to marine disasters.

3.2. Grid Search Algorithm

For RF, the number of decision trees (n_estimators) and the number of splits per tree (m_features) are both important parameters that affect the performance of the RF model [30,45]. The parameters of the RF model can be determined empirically but often do not result in optimal performance. In this paper, the parameters were optimized using the grid search method based on the OOB error rate. Grid search refers to gridding the variable region, traversing all grid points, solving for the objective function values that satisfy the constraint function, and finally comparing to select the optimal point. However, it takes much training time to travel all points on the grid. To improve training speed, this article enhanced the traditional algorithm for optimizing grid search parameters. Firstly, the grid was divided into a large range with big steps, and the optimal point was selected by coarse search. Secondly, we used small steps to divide the grid near the optimal point to make the grid division denser, and the optimal point was selected by the detailed search. Finally, the improved algorithm to optimize grid search parameters was combined with RF to ensure the accuracy and relative stability of the assessment results.

3.3. Model Performance Indicators

In order to evaluate the performance of the model, this study also used the commonly used regression model evaluation indicators of Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), coefficient of determination (R^2) and Root Mean Squared Error (RMSE). Formulas are expressed as Equations (1)–(4):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{1}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=2}^{n}(y_i - \overline{y}_i)^2} \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4}$$

4. Results and Discussion

4.1. CMDRI Grading Standards

This study used the natural breakpoint method [46] to classify all indicators of the eight cities from 2000 to 2019 to obtain simulation intervals of each grade after establishing the RF model [32]. By using the clustering idea of the natural breakpoint method, each indicator was divided into five grades, and the grade thresholds of each indicator were statistically obtained. The grading results are shown in Table 2.

Table 2. CMDRI grading standards.

Indicators	I	II	III	IV	V
A11	[439, 870)	[870, 1328)	[1328, 3098)	[3098, 4490)	[4490, 6484]
A12	[2.50, 2.70)	[2.70, 2.96)	[2.96, 3.34)	[3.34, 3.74)	[3.74, 4.24]
A13	[0.66, 0.97)	[0.97, 1.75)	[1.75, 1.89)	[1.89, 2.04)	[2.04, 2.21]
A21	[97.00, 100.15)	[100.15, 103.27)	[103.27, 107.57)	[107.57, 113.76)	[113.76, 166.50]
A31	[8.63, 10.29)	[10.29, 11.28)	[11.28, 12.77)	[12.77, 14.20)	[14.20, 16.75]
A32	[1.59,4.38)	[4.38, 8.15)	[8.15, 10.53)	[10.53, 12.99)	[12.99, 16.37]
A41	[0.15, 0.22)	[0.22, 0.29)	[0.29, 0.35)	[0.35, 0.41)	[0.41, 0.49]
B11	[0.39, 1.48)	[1.48, 2.87)	[2.87, 4.72)	[4.72, 8.43)	[8.43, 11.76]
B12	[95.88, 1066.92)	[1066.92, 2133.4)	[2133.40, 3529.38)	[3529.38, 5877.06)	[5877.06, 9366.03]
B21	[1.70, 3.21)	[3.21, 4.52)	[4.52, 5.92)	[5.92, 7.92)	[7.92, 10.02]
B22	[35.49, 60.76)	[60.76, 85.52)	[85.52, 118.52)	[118.52, 176.21)	[176.21, 222.73]
B23	[1.70, 3.21)	[3.21, 4.52)	[4.52, 5.92)	[5.92, 7.92)	[7.92, 10.02]
C11	[12,353, 42,555)	[42,555, 72,363)	[72,363, 105,909)	[105,909, 143,880)	[143,880, 203,489]
C12	[121, 4158)	[4158, 9283)	[9283, 16,896)	[16,896, 26,927)	[26,927, 38,155]
C13	[6860, 19,014)	[19,014, 32,381)	[32,381, 48,695)	[48,695, 73,615)	[73,615, 285,567]
C14	[6.23, 621.84)	[621.84, 1634.22)	[1634.22, 2783.58)	[2783.58, 4585.55)	[4585.55, 7165.10]
C21	[42, 1653)	[1653, 3543)	[3543, 5938)	[5938, 8871)	[8871, 13,066]
C31	[52.59, 70.25)	[70.25, 80.54)	[80.54, 86.45)	[86.45, 91.71)	[91.71, 95.34]
C41	[1.61, 2.26)	[2.26, 2.73)	[2.73, 3.31)	[3.31, 3.97)	[3.97, 4.90]
C51	[4.59, 403.50)	[403.50, 872.31)	[872.31, 1863.65)	[1863.65, 3688.69)	[3688.69, 5374.74]
D11	[0.11, 0.93)	[0.93, 1.87)	[1.87, 4.45)	[4.45, 6.45)	[6.45, 8.01]
D12	[1.69, 5.81)	[5.81, 9.74)	[9.74, 15.10)	[15.10, 20.91)	[20.91, 26.85]
D21	[18.21, 84.08)	[84.08, 138.28)	[138.28, 268.59)	[268.59, 557.54)	[557.54, 817.70]
D22	[356, 3962)	[3962, 7483)	[7483, 16,077)	[16,077, 26,736)	[26,736, 48,669]
D31	[11.80, 19.21)	[19.21, 25.04)	[25.04, 30.63)	[30.63, 37.71)	[37.71, 46.8]
D41	[124, 572)	[572, 1161)	[1161, 1709)	[1709, 2254)	[2254, 3449]
E11	[1.54, 5.60)	[5.60, 9.50)	[9.50, 12.30)	[12.30, 15.10)	[15.10, 18.60]
E12	[22.2, 28.44)	[28.44, 34.50)	[34.50, 39.20)	[39.20, 42.80)	[42.80, 46.67]
E21	[0.01, 0.10)	[0.10, 0.20)	[0.20, 0.30)	[0.30, 0.45)	[0.45, 0.75]
E22	[2, 52)	[52, 159)	[159, 338)	[338, 580)	[580, 834]
E23	[312.60, 686.20)	[686.20, 1104.60)	[1104.60, 1532.10)	[1532.10, 2067.10)	[2067.10, 2939.70]
E24	[-15, 33)	[33, 63)	[63, 85)	[85, 110)	[110, 153]
E31	[0.06, 0.09)	[0.09, 0.21)	[0.21, 0.24)	[0.24, 0.60)	[0.60, 0.72]
E32	[154, 230)	[230, 905)	[905, 1594)	[1594, 2211)	[2211, 2444]

Based on the grading standards of each indicator, five standard level intervals (I-V) of CMDRI were obtained. Then, 500 samples were randomly generated within each level interval, with a total of 2500 samples being generated. Additionally, 1, 2, 3, 4, and 5 were used as the expected outputs of the levels of CMDRI. There were 350 training samples and 150 test samples randomly selected from each level. Therefore, a total of 1750 training samples and 750 test samples were obtained.

4.2. Parametric Optimization

Based on the grid search method, the optimal configuration of the RF model parameters was obtained in this study. Firstly, the coarse search was performed with a large step size, the number of decision trees was set in the range of $50 \leq$ n_estimators ≤ 3000 and the step size was set to 100. The splitting variables were set in the range of $5 \leq$ m_features ≤ 34 and the step size was set to five. The results are shown in Figure 2a. The grid refinement was performed around the optimal points n_estimators= 2450 and m_features = 15 obtained from the coarse search. n_estimators was taken in the range of $2350 \leq$ n_estimators ≤ 2550 with the step size set to 20, and m_features was taken in the range of $150 \leq$ m_features ≤ 20 with the step size set to 1. From Figure 2b, it can be seen that when the number of decision trees n_estimators = 2450 and the number of splits m_features = 15, the generalization error of the RF is still the smallest at 0.0056. When the number of decision trees is greater than 2450, the OOB error rate generally tends to remain stable, while if the number of splits is greater than 15, the OOB error rate increases and the model performance decreases instead. This indicates that the performance of RF model does not improve infinitely with an infinite number of decision trees and splits. Therefore, the parameter configuration of n_estimator = 2450 and n_features = 15 was chosen for model construction in this study.

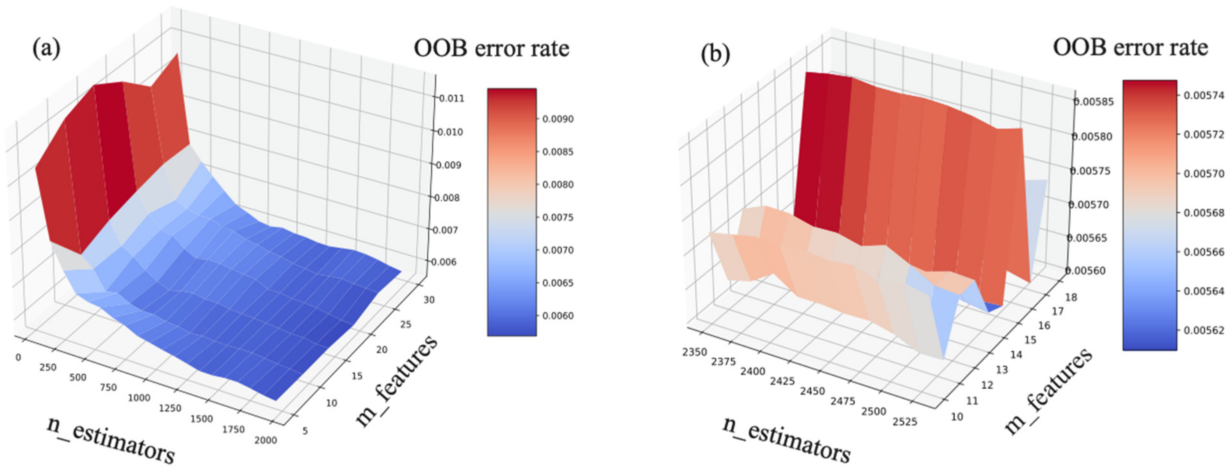

Figure 2. Parameter optimization in the RF model based on grid search: (**a**) Coarse search result. (**b**) Detailed search result.

4.3. CMDRI Evaluation Results

4.3.1. Time Variability Analysis of CMDRI

The simulation model was established after training and learning, and five simulation grades (I–V) were obtained after the simulation, as shown in Table 3. Finally, using the data of eight cities from 2000 to 2019, the simulation model was run to obtain the CMDRI values. The resilience grades of each city were obtained according to Table 3.

Table 3. CMDRI grade simulation interval of RF model.

Grade	I	II	III	IV	V
Interval	[1, 1.466)	[1.466, 2.483)	[2.483, 3.364)	[3.364, 4.549)	[4.549, 5]

The results of the temporal variability in CMDRI of eight Chinese coastal cities that are proposed to build a global maritime capital are shown in Figure 3. Based on Table 3, the average values of CMDRI from 2000–2004, 2005–2009, 2010–2014, 2015–2019 and 2000–2019 were calculated and also rated according to Table 3 to further analyze cities' intrinsic CMDRI performance. The results are presented in Table 4.

Table 4. Evaluation results and grades of CMDRI.

City	Evaluation Results					Evaluation Classes				
	2000–2004	2005–2009	2010–2014	2015–2019	2000–2019	2000–2004	2005–2009	2010–2014	2015–2019	2000–2019
Dalian	1.827	1.900	2.381	2.528	2.159	II	II	II	III	II
Tianjin	2.042	2.332	2.773	2.994	2.536	II	II	III	III	III
Qingdao	1.895	2.132	2.471	2.811	2.327	II	II	II	III	II
Shanghai	2.467	2.845	3.124	3.477	2.978	II	III	III	IV	III
Zhoushan	1.773	1.914	2.128	2.464	2.070	II	II	II	II	II
Ningbo	1.912	2.124	2.509	2.864	2.352	II	II	III	III	II
Shenzhen	2.808	3.285	3.590	3.708	3.348	III	III	IV	IV	III
Guangzhou	2.247	2.523	2.986	3.248	2.751	II	III	III	III	III

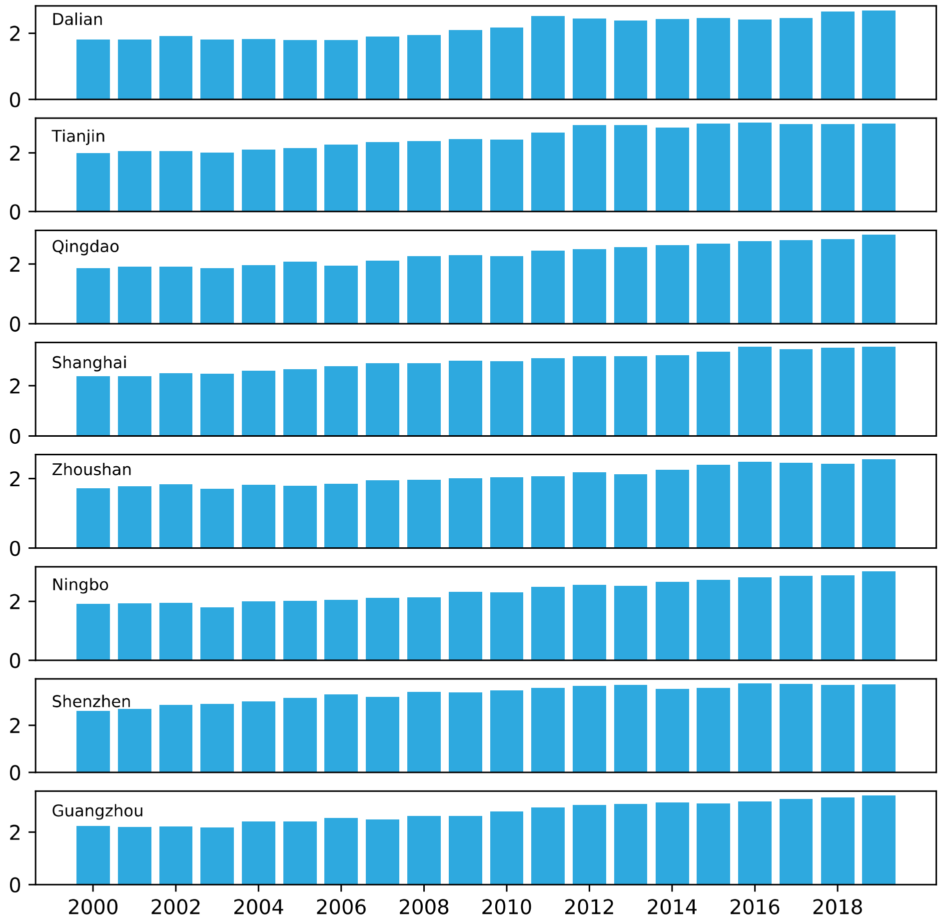

Figure 3. Time variability evaluation results of CMDRI.

Overall, the CMDRI values of all eight coastal cities show an upward trend, which holds at the 95% confidence level of Mann Kendell's trend test ($p < 0.001$). Among them, Shenzhen has the highest CMDRI level with an annual average CMDRI value of 3.348, followed by Shanghai and Guangzhou with 2.978 and 2.751, respectively. Zhoushan is the city with the lowest CMDRI value, and the annual average CMDRI value is 2.070. Dalian, Qingdao, Zhoushan, and Ningbo have relatively low disaster resilience grades, all grade II, while Tianjin, Shanghai, Shenzhen, and Guangzhou were all grade III.

From 2000 to 2004, Shenzhen's CMDRI value was 2.808, the only grade III of the eight coastal cities, while the remaining cities were all grade II. From 2005 to 2009, Shenzhen's CMDRI value was 3.285, while Shanghai and Guangzhou's CMDRI values were 2.845 and 2.523, both of which changed their grades from II in 2000–2004 to III. From 2010–2014, Shenzhen's CMDRI value was 3.590, and its grade rose from previous III to IV. At the same time, Tianjin and Ningbo's CMDRI values were 2.773 and 2.509, respectively, and their grades changed from previous II to III. Shanghai's CMDRI value for 2015-2019 was 3.477, with their grade shifting from III to IV from 2010–2014. Shenzhen remained unchanged at grade IV, Tianjin and Ningbo remained unchanged at grade III, while Qingdao and Dalian had a CMDRI value of 2.811 and 2.528, shifting from its previous grade II to III. That is to say, except for Zhoushan, the rest of the cities achieved an increase in disaster resilience levels.

Second, Shenzhen, Guangzhou and Shanghai, located in the southeast coastal region, have higher CMDRI levels than Dalian, Tianjin and Qingdao, located in the Yellow and Bohai Sea region. According to the China Marine Disaster Bulletin, compared to the Yellow and Bohai Sea region, the southeast coastal region suffers more serious losses to marine disasters [47]. The higher the frequency and severity of marine disasters, the richer the experience in preventing and resisting marine disasters, which to a certain extent will contribute to the improvement of the urban marine disaster recovery capacity in all dimensions. Therefore, the CMDRI of Guangzhou, Shenzhen and Shanghai is relatively high. In contrast, although Ningbo and Zhoushan located in Zhejiang Province are severely affected by marine disasters, they are relatively weaker in terms of marine disaster resilience due to their city size and the relatively insignificant human and economic capitals. In particular, Zhoushan is an archipelago city with the longest coastline among the coastal cities, leading to a more extensive exposure to marine disasters and affecting the overall improvement of coastal marine disaster resilience. The Bohai Sea region mainly suffers from marine disasters such as extratropical storm surges and sea ice. Dalian, which is located in the Bohai Bay, has a long coastline, and its exposure to marine hazards is relatively large. It is the less resilient city among the three cities in the Yellow and Bohai Sea region.

4.3.2. Key Factors Analysis of CMDRI

The importance ranking of each indicator was obtained according to the permutation importance, as shown in Figure 4. Among them, the coastline length has the greatest influence on the evaluation results, followed by the population burdened by each employed person, which has similar importance results. The indicators ranked third to seventh are the coverage rate of urban green area, number of beds in health facilities, total import and export, total fixed asset investment and the percentage of population with high school education and above, which have an impact on the evaluation results between 3.1% and 3.2%, and the remaining indicators on the accuracy of the model contribute less than 3.1%. To further identify the key factors that contribute more to disaster resilience in the evaluation process, this paper set the threshold of the number of indicators that can cover more than two-thirds of the importance of the whole indicator system as key factors, according to the principle of the top two-thirds. The top 27 index factors in the five capitals were identified as key factors, covering more than 80% importance of the entire index system, as can be seen in Figure 5.

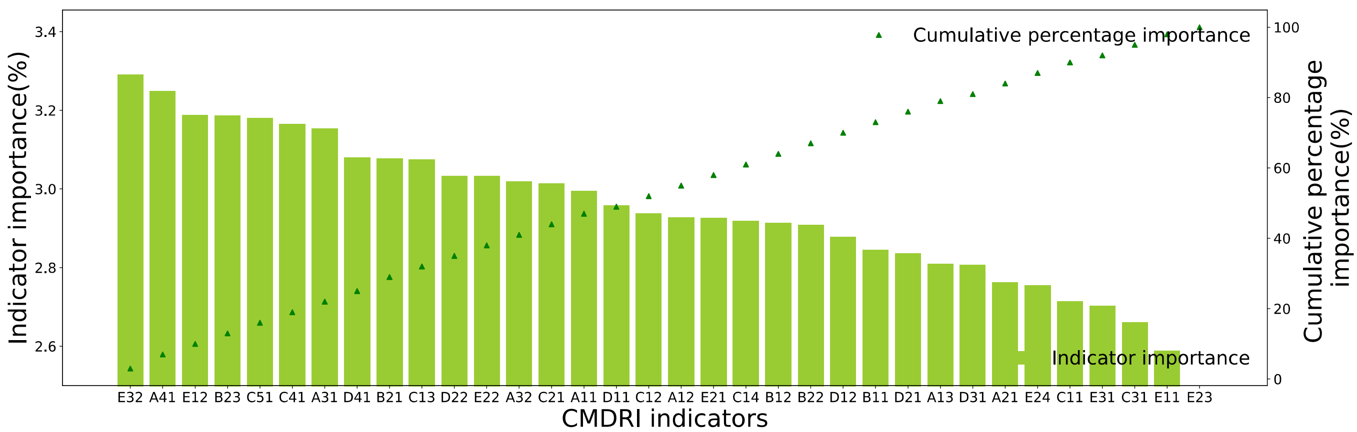

Figure 4. Permutation importance of each indicator in the RF model.

Specifically, economic capital has the largest share in the key factor analysis at 18.3%. The trade level, investment level, economic diversity, GDP and income were identified as key indicators influencing the CMDRI, which reflect the city's ability to provide financial relief to the disaster-affected population and recover quickly from the disaster. Cities cannot prevent and protect themselves from marine disasters without financial investment in the early stages. Therefore, the economic capital of a city will directly mitigate the impact of disasters from the pre-disaster and post-disaster periods, and quickly restore normal socio-economic life. Human capital accounted for 18.2% of the analysis of key factors. Similar to economic capital, it can also support marine disaster resilience in all periods of marine disaster risk management. This study identifies demographics, educational attainment, gender structure and age structure as important factors in human capital. Among them, reducing the employment burden population, increasing the level of education, increasing the number of people per household and increasing the young adult labor can improve the city's ability to cope with marine disaster recovery in terms of both quantity and quality of the labor force, respectively.

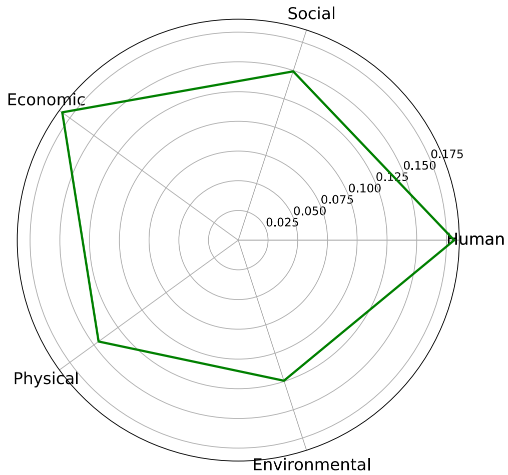

Figure 5. Key factor results of CMDRI.

Physical capital and social capital each account for 17.6% and 14.9% of the key factors, respectively. Among the physical capital, the critical capital represented by water and electricity and the basic capital represented by drainage capacity and road length are important influencing factors. They represent the foundational facilities that cities need in order to maintain normal production and living conditions in the face of marine disasters. In addition, the overall disaster evacuation sites represented by temporary evacuation sites and residential conditions are also the main influencing factors. For social capital, the level of social assistance represented by the number of beds, the number of health facilities and the number of technicians occupies a key position in social capital, representing the city's ability to have enough medical capital to maintain normal social order in a disaster event. Meanwhile, the information communication capacity represented by the number of telephone users and the transportation capacity, represented by the number of civilian vehicles, can play a role in disaster warning before a disaster and evacuation and rescue transportation after a disaster, which are also important factors of resilience. Environmental capital represents 12.4% of the analysis of key factors. Among environmental capital, conditions such as coastline length, wastewater discharge and sewage treatment capacity are important influencing factors, which have an intuitive and definite causal relationship with the occurrence of marine disasters such as storm surges and red tides. Therefore, if we can effectively control these key factors, it will help to improve the resilience of marine disasters in a quick and effect way. At the same time, as the "shock absorber" of urban disaster risk, the protection and improvement of environmental resources such as the coverage rate of urban green area should not be neglected.

4.4. Model Performance Comparison

4.4.1. Comparison of Model Fitting Performance

To compare the fitting ability and precision of the RF, Support Vector Machine (SVM) and Linear Regression (LR) were used as comparison models. As shown in Table 5, the MAE, MAPE, R^2 and RMSE of the RF model are 0.0006, 0.0006, 0.9999 and 0.0052, respectively, which indicate that the RF model has high evaluation accuracy and can be used as an evaluation method for the CMDRI of China.

Table 5. Performance indicators of different models.

Model	MAE (%)	MAPE (%)	R^2	RMSE (%)
RF	0.1847	0.0717	0.9999	0.5840
SVM	9.8016	4.7839	0.9924	12.3307
LR	5.4358	2.5788	0.9977	6.8167

In order to analyze the stability of the RF model and prevent the overfitting, this study further conducted a five-fold cross-validation, as shown in Table 6. The OOB error rate of the model ranges from 0.4910% to 0.5663%, with an average value of 0.5232%, providing reliability and rationality for the RF model.

Table 6. K-fold Validation results of random forest (RF) model.

Fold	K = 1	K = 2	K = 3	K = 4	K = 5	Average
OOB error (%)	0.5663	0.4910	0.5185	0.5038	0.5363	0.5232

4.4.2. Comparison of Model Evaluation Results

To evaluate the stability of the RF model, the CMDRI values of RF, SVM and LR were obtained, as well as the mean value of three models. The RMSE of the evaluation results were calculated separately from the mean value of the results, as shown in Table 7. It can be seen from Table 7 that the RF model has the smallest RMSE value of 20.6786%, compared to the SVM model and the linear model. Consequently, the RF model evaluation results are considered stable.

Table 7. Comparison of evaluation results of CMDRI under different models.

Model	RF	SVM	LR
RMSE (%)	20.6786	47.3769	33.9892

5. Conclusions

The frequent outbreak of marine disasters in the context of global warming poses a serious threat to the sustainable development of coastal areas and the construction of global maritime capitals. Marine and coastal management and marine disaster resilience assessment of maritime capitals have become the research focus. For eight coastal cities in China that propose to build global maritime capital, this paper innovates by constructing and calculating the CMDRI for China's coastal cities, evaluating marine disaster resilience and identifying key factors first using the RF model. The results show that:

(1) The overall level of CMDRI in each city is at a steady increase, with the highest level in Shenzhen and the relatively lowest level in Zhoushan throughout the all years. With the exception of Zhoushan, the remaining cities have achieved an increase in CMDRI grades during 2000–2019. Shenzhen, Shanghai and Guangzhou belong to the southeast coastal region with relatively high CMDRI, while Dalian, located in the Yellow Bohai Sea region, is relatively lower than Tianjin and Qingdao.

(2) In the identification of key factors, coastline length, the population burdened by each employed person, coverage rate of urban green area, number of beds in health facilities, total import and export, total fixed asset investment and the percentage of population with high school education and above are the indicator factors ranked high in the importance of evaluation results. Economic and human capitals are the most essential urban capital in the identification of key factors, followed by physical and social capitals, with environmental capital having the smallest share.

(3) Compared to SVM and LR models, the fitting accuracy and generalization ability of the RF model are better than other models. In addition, the RF model has better stability in the assessment process, and the results are more reasonable. The RF performs well in

assessing and identifying the CMDRI, and the developed method can be transferred to other fields of disaster resilience and regional sustainability assessment.

Determining the level of city resilience to marine hazards and key factors will provide strategic direction for emergency policymakers to reduce the negative impacts of disasters. According to the results, managers of coastal cities can make full use of location advantages to develop the economy and attract labor power. Specifically, the following suggestions are proposed: (1) reduce the burden of the employed population while improving the quality of the population; (2) enhance the level of urban trade and investment; (3) strengthen the city's medical help capacity and the level of urban green area; (4) pay attention to the supervision and warning of marine disasters in cities with long coastlines, such as Zhoushan and Dalian. This study provides a reference for coastal cities to incorporate marine disaster resilience into disaster risk management plans. Improving the key factors of CMDRI and ensuring rapid regulation will have a significant and long-lasting driving effect and jointly promote the improvement of marine disaster resilience in coastal cities for the smooth construction of global maritime capital. There will be other coastal cities considered for the construction of global maritime capital. This study has proved that the CMDRI has good city adaptability and can be applied to other coastal cities in China to assess marine disaster resilience. At the same time, our results are also of practical value for other coastal areas around the world that rely on marine resources but often suffer from marine disasters, such as the Caribbean and the Mediterranean regions. By identifying the level of disaster resilience and key impact factors, research results will have excellent references for marine disaster management and the sustainable development of coastal cities.

Finally, further studies could improve the potential limitations of this study. Due to the inconsistencies in the timing length and statistical caliber of the statistical data in various cities, some indicators referring to organizational beliefs, disaster warning capabilities and so on could not be included in the study. However, with the continuous improvement of marine disaster monitoring, socioeconomic development, and the utilization of predictive modeling, such as grey models [48], it will be possible to break through data availability limitations and consider an appropriate increase in indicators of the marine disaster resilience system.

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