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Exploring the Influence of the Digital Economy on Marine Pollution Mitigation: A Spatial Econometric Study of Coastal China

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Abstract: This work employs the spatial econometric model to explore the potential relation between the condition of marine ecosystems and the rapid development of the digital economy (DE), focusing on the coastal area of China. While the environmental benefits of the DE are well studied regarding the land and atmospheric pollution, its influence on marine pollution (MP) remains underexplored, and this work aims to fill in this gap. By analyzing panel data from 42 coastal cities in China using a spatial Durbin model to examine both the direct and indirect impacts of the DE on MP, the results highlight the positive role that the DE plays in reducing MP, benefitting not only the local marine environments but also those of neighboring areas through non-negligible spatial spillover effects. In addition, we find a non-linear, inverted U-shaped relationship between the DE and MP. These results are further confirmed through extensive robustness tests. This work enriches the field of environmental economics by reporting the first empirical study on the marine benefits of the DE and offers policy recommendations to optimize digital technologies for marine environmental preservation.

Keywords: digital economy; marine pollution; spatial econometric analysis; spillover effects

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1. Introduction

In recent years, the issue of environmental pollution has attracted considerable research attention worldwide due to its urgency and complexity [1–3]. Numerous studies have evaluated the critical determinants of environmental degradation from both the microscopic and macroscopic perspectives. The emergence of the digital economy (DE), characterized by rapid technological progress and expanded digital integration, has sparked significant interest in its environmental consequences. Most existing research in this direction has focused on the DE's capacity to alleviate land-based and atmospheric pollutants. This focus is rational and natural, as advancements in the DE enhance resource management, boost energy efficiency, and foster innovative sustainable practices, collectively aiding in the reduction of various pollution types.

At the same time, much research attention is also paid to the third kind of environmental system—the marine system [4–9]. It is well recognized that marine ecosystems are essential for global biodiversity and the sustenance of human communities, especially for the over 40% of the world's population residing in coastal zones. Recent studies have extensively examined marine pollution (MP) from various angles. For instance, investigations into the origins of coastal MP by Shen et al. [10] have identified local governmental competition in China as a contributing factor, with more pronounced effects observed under intense fiscal pressures. Similarly, Jiang and Li [11] demonstrated that the GDP evaluation systems employed by local governments exacerbate MP. Port development and operations also significantly impact marine environments. Agarwala [12] highlighted the environmental degradation caused by seaport activities, emphasizing the need for sustainable practices to mitigate these effects. Another significant contributor to MP is the rapid urbanization process of coastal cities. Freeman et al. [13] indicated that pollution resulting from urbanization adversely impacts coastal water quality through mechanisms such as river inputs, urban runoff, and port discharges. Additionally, Garcés-Ordóñez et al. [14] found that the development of coastal tourism has led to significant marine pollution, which in turn affects water quality. Trade openness and industrialization play further key roles in MP. Ullah et al. [15] analyzed the relationship between trade, industrialization, and MP, demonstrating that these factors markedly increase MP due to industrial waste water that contains heavy metals, organic compounds, and toxic chemicals, all of which cause marine pollution if not properly treated. Issifu and Sumaila [16] discussed the severe impact of plastic waste on marine ecosystems, stressing the importance of effective policy interventions to manage and reduce plastic pollution. Moreover, Alam et al. [17] discussed the inadequacies of marine environmental governance—including the negative externalities of marine ecological protection, the confusion within marine management systems, and the lack of social participation mechanisms—as important reasons for the increasing MP.

Despite the significant economic factors influencing MP outlined previously, the specific perspective of the digital economy (DE) and its potential influence on MP remains unexplored. Considering the DE's rapid evolution and its proven effects on terrestrial and atmospheric pollution, it is particularly crucial to investigate whether the DE similarly influences MP as well. As global industries increasingly adopt digital technologies—a transformation that directly and indirectly affects marine environments—it becomes essential to explore this relationship. This study addresses this question by focusing on how the DE influences MP in costal China and aims to provide insights for the sustainable management of both the digital economy and marine ecosystems.

To achieve this objective, we analyzed panel data from 42 coastal cities in China, spanning from 2006 to 2015. Using the concentration data of four primary marine pollutants, we constructed a comprehensive index for MP. Similarly, we formulated a DE index from various indicators. Benefitting from previous studies, we evaluated the DE's influence on marine environments using the spatial econometric techniques. Our findings indicate that the DE plays a significant role in mitigating MP through both direct and indirect effects, as supported by various robustness checks, and lead to several policy recommendations.

The structure of this paper is organized as follows. Section 2 elaborates on the construction of the MP index from four principal marine pollutants and establishes the spatial autocorrelations among these indices across the coastal cities, laying the foundation for the spatial econometric analysis. Section 3 describes the used data in detail, highlighting the DE index as the main variable of interest, along with other control variables. Section 4 provides step-by-step tests to pick out the most appropriate spatial econometric model and reaches toward the major finding of this work, which is followed by various robustness checks. Finally, Section 5 summarizes our results and leads to the discussion in Section 6.

2. Marine Pollution Index and Autocorrelation

2.1. Construction of Marine Pollution Index

For the purpose of assessing the impact of the digital economy (DE) on marine pollution (MP) through spatial analysis, the first task is to develop an accurate MP index to represent the overall sea water quality. In the literature, the construction of an MP index is not unique. Some studies, such as Ref. [18], used the nitrogen as the single index; Refs. [19,20] used the industrial wastewater discharged directly into the sea; Ref. [21] used the proportion of four inferior types of seawater quality to measure marine pollution, and so on. Considering the data coverage and availability, we follow the methodology in Ref. [22] to construct the MP index using concentration measurements of four key marine pollutants found in coastal waters: reactive phosphate (RP), inorganic nitrogen (IN), chemical oxygen demand (COD), and petroleum hydrocarbon (PH). Notably, IN is considered the primary pollutant and often used as the sole indicator of MP in existing works [18]. The formula for calculating the representative MP index is:

$$MP_{it} = \gamma_1 RP_{it} + \gamma_2 IN_{it} + \gamma_3 COD_{it} + \gamma_4 PH_{it} \quad (1)$$

Here, MP_{it} stands for the MP index for the i-th city in the t-th year, whose units are all mg/L, and γ_i denotes the weight of each pollutant. The data for these pollutants were collected from 42 coastal cities in China over the period from 2006 to 2015 from the *China Coastal Environmental Quality Bulletin*. The weight γ_i is assigned as the average value of the point exceedance rate of each pollutant in the considered time period, which leads to [22]: γ_1 = 0.63, γ_2 = 0.03, γ_3 = 0.29 and γ_4 = 0.05. The resultant MP indices will be used as the dependent variables in our spatial econometric analysis. This dataset includes most of China's coastal areas, providing a comprehensive system appropriate for spatial econometric exploration. This approach is consistent with the methodologies employed in Refs. [18–20,22,23]. For ease of reference, a map showing the geographic distribution of the 42 cities selected for this study is provided in the inset of Figure 1.

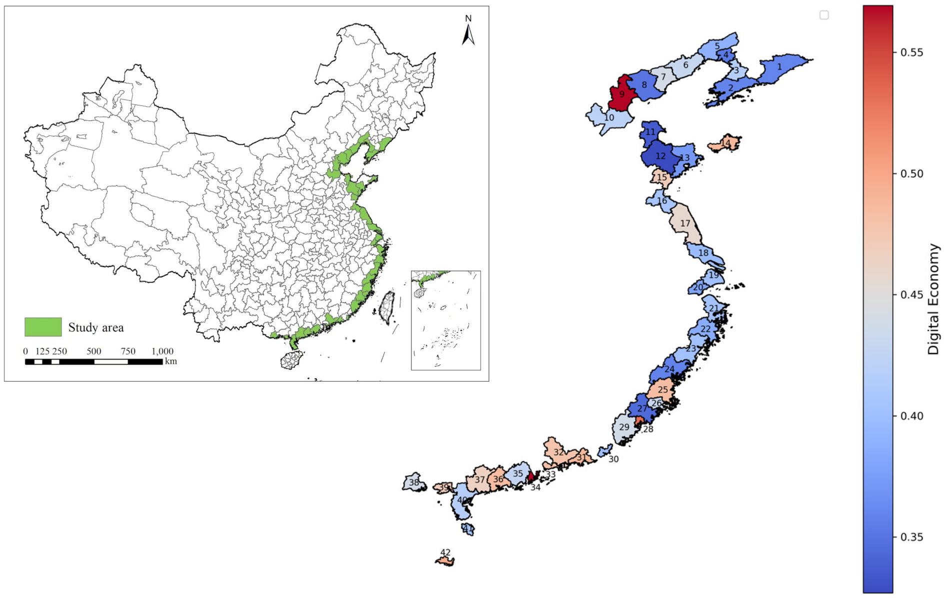


Figure 1. Mapping the digital economy index in 2015, where the name of each city is given in the appendix with corresponding index number. Inset: A depiction of the geographical distribution of the 42 selected coastal cities.

2.2. *Spatial Autocorrelations among Coastal Marine Pollutions*

Once the representative MP indices are established, the subsequent task is to confirm their spatial autocorrelations—a necessary step for any spatial econometric analysis. This verification is conducted using the Moran's I tests. Moran's I index, which quantifies the overall spatial correlation among the MP indices, is computed as follows:

$$\mathrm{I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\mathrm{S}^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (2)$$

Here, $S^2 = \sum_{i-1}^{n}(x_i - \overline{x})^2/n$, denoting the sample variance, and w is the spatial weight matrix that defines the spatial relationships between the i-th and j-th cities. Initially, a straightforward yet effective weight configuration is used, i.e., $w_{ij} = 1$ if the i-th and j-th cities are neighbors, and $w_{ij} = 0$ otherwise. Different configurations of w will be tested in the subsequent robustness analysis.

The Moran's I values range from −1 to 1, where positive or negative values indicate the presence of positive or negative spatial autocorrelations, respectively. Table 1 presents the global (here the term "global" refers to the overall spatial autocorrelation across all the selected coastal cities) Moran's I outcomes for the MP indices of the 42 selected coastal cities in China from 2006 to 2015. Notably, aside from the year 2008, the Moran's I values have remained positively significant at the 1% level, indicating substantial positive spatial correlations in MP throughout these coastal areas.

Table 1. Global Moran's I statistics for marine pollution, 2006 to 2015.

Year	**2006**	**2007**	**2008**	**2009**	**2010**
Moran's I	0.411 ***	0.414 ***	−0.008	0.327 ***	0.391 ***
Year	**2011**	**2012**	**2013**	**2014**	**2015**
Moran's I	0.262 **	0.370 ***	0.383 ***	0.402 ***	0.454 ***

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

3. Data Description

3.1. Core Explanatory Variable: The Digital Economy Index

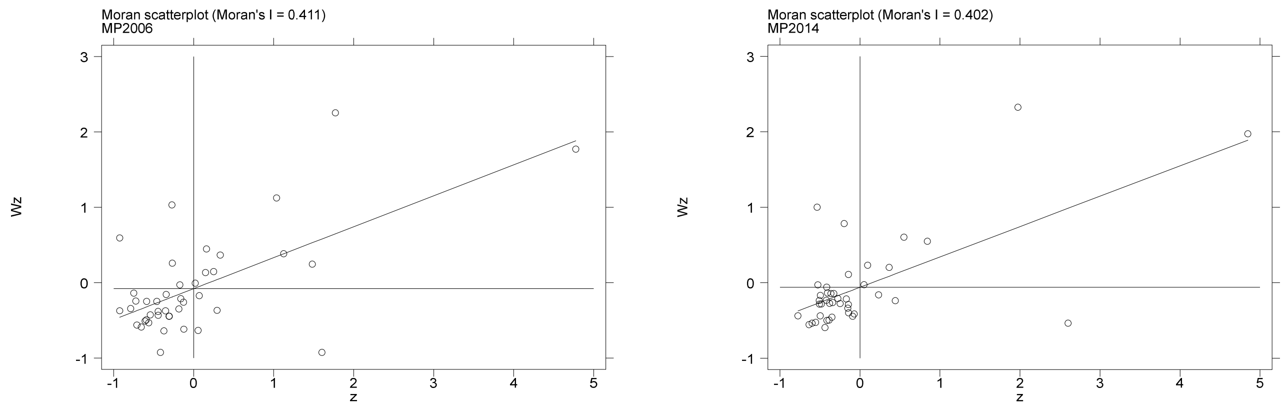
Based on the findings in the preceding section, we decided to use a spatial econometric model to explore how the DE impacts marine pollution (MP). Consequently, our next step involves creating a suitable index to quantify the DE's progress at the municipal level. To provide a thorough and precise index construction, and given the data at our disposal, we follow the guidance in Ref. [24] to select four key components of the DE index: internet penetration rate, employment levels in technology sectors, output from related industries, and mobile phone penetration rate. Detailed definitions of these components can be found in Table 2. We then normalize these metrics and construct a composite DE index for each city with the standard entropy method [24]. This composite DE index will serve as the principal explanatory variable in our subsequent analyses. To visually illustrate this, a heatmap displaying the DE indices' distribution across the 42 selected cities for the year 2015 is provided in Figure 1, where higher DE index values are marked with the red color and indicate more advanced digital development in corresponding city, and the opposite applies to the blue color.

Table 2. Composition of the DE index.

Primary Index	**Secondary Index**	**Index Interpretation**
Digital economy development level	Internet penetration rate	Number of broadband internet connections per 100 people
	Industry employment ratio	Share of computer service and software industry workers among urban employment
	Business output	Per capita volume of telecommunications services
	Mobile phone usage	Mobile phone subscriptions per 100 people

To further analyze the spatial heterogeneity, we examine the Moran scatterplots. These plots categorize into four distinct quadrants or clusters as follows: high–high (HH), low–high (LH), low–low (LL), and high–low (HL). The HH cluster represents areas where high values are surrounded by other high-value locations; conversely, the LL cluster indicates areas with low values surrounded by similar low-value regions. The HL and LH clusters are interpreted analogously. Positive spatial autocorrelations in MP would typically result in a concentration of data points in the HH and LL quadrants.

Interestingly, the behavior of the Moran scatterplots is consistent across the years, with the exception of 2008. Therefore, in Figure 2, we display the scatterplots for the years 2006 and 2014 as illustrative examples. As hypothesized, the majority of data points cluster in the HH and LL quadrants, confirming the presence of positive regional correlations in marine pollution, which strengthens the findings of the global Moran's I assessments.



(a) (b)

Figure 2. Moran scatterplots for marine pollution in the years 2006 (**a**) and 2014 (**b**).

In conclusion, the data from the Moran's I values and the scatterplots validate the existence of positive spatial autocorrelation among the MP indices in coastal regions of China. This substantiates the later application of spatial econometric models to explore the dynamics between the DE and MP. Before that, we first outline the explanatory and control variables that will be employed in our econometric analysis.

3.2. Control Variables

In response to the inherent issue of omitted variable bias and reflecting the specific conditions of China's coastal MP as reported in prior studies [25,26], we have chosen the set of control variables listed below.

- Economic Growth (EG): This is quantified by the per capita GDP of each city, incorporating a quadratic term to consider potential non-linear effects, as suggested by the environmental Kuznets curve (EKC) hypothesis [27].
- Urbanization Rate (UR): Defined by the ratio of urban to permanent residents. The growth in population and urban development in coastal areas indicates increased economic activities, influencing the marine environment, as noted in previous research [13,28].
- Population Density (PD): Calculated as the number of people per square kilometer. High population density is a primary contributor to coastal water pollution, which escalates sewage discharge and intensifies ocean pollution.
- Energy Efficiency (EE): Measured by the energy consumption per unit of GDP in each city, the effects of which on MP have been reported in Ref. [29].
- Industrial Structure (IS): Defined as the ratio of secondary industry output to the city's total GDP. The impact of industrial activities on the coastal marine environment is transparent and well recognized.
- International Openness (IO): Defined by the share of utilized foreign direct investment in the city's GDP.
- Government Intervention (GI): This is represented by the ratio of government fiscal spending to the city's GDP and introduced as a measure of governmental activity.
- Marine Economic Development (MED): This is evaluated using gross ocean product data at the provincial level due to the absence of city-specific data, following the methodology in Ref. [22]. A detailed list of the cities and corresponding provinces is provided in Appendix A.

3.3. Data Source and Description

As outlined in the preceding section, data concerning marine pollutants were sourced from the China Coastal Environmental Quality Bulletin, covering the years 2006 to 2015; consequently, we have compiled panel data for 42 cities within this timeframe. Data pertaining to the DE indicators were derived from the China City Statistical Yearbook. Additional variables, such as the population density (PD), economic Growth (EG), urbanization rate (UR), industrial structure (IS), energy efficiency (EE), international openness (IO), and government intervention (GI), were similarly sourced from the China City Statistical Yearbook and Statistical Bulletin. Data on marine economic development (MED) were collected from the China Marine Statistical Yearbook. All the monetary variables were deflated to the base-year prices of 2006. For the purposes of our econometric analysis, logarithmic transformations were applied to all the variables. The quantitative descriptive statistics for these variables are provided collectively in Table 3.

Table 3. Descriptive statistics for all the employed variables ("ln" denotes the natural logarithm).

Variable Type	Variable Name	Symbol	Observations	Mean	Standard Deviation	Min	Max
Explained Variable	Marine pollution	*lnMP*	420	−1.930	0.738	−4.010	0.380
Core Explanatory Variables	Digital economy	*lnDE*	420	−2.468	0.852	−5.026	−0.046
	Quadratic term of digital economy	$(lnDE)^2$	420	6.814	4.559	0.002	25,263
Control Variables	Economic growth	*lnEG*	420	10.646	0.597	9.086	12.066
	Quadratic term of economic growth	$(lnEG)^2$	420	113.699	12.724	82.556	145.581
	Urbanization rate	*lnUR*	420	−0.260	0.124	−0.575	0
	Population density	*lnPD*	420	6.266	0.579	4.890	7.882
	Energy efficiency	*lnEE*	420	−1.064	1.071	−3.878	1.580
	Industrial structure	*lnIS*	420	3.881	0.212	2.958	4.390
	Degree of openness to the outside world	*lnIO*	420	−3.787	1.013	−6.640	−2.028
	Government intervention	*lnGI*	420	−2.166	0.344	−3.155	−1.275
	Marine economic development	*lnMED*	420	9.823	0.514	8.577	10.847

4. Empirical Evaluation

4.1. Spatial Durbin Model

Considering the spatial autocorrelations among the marine pollution indices (MPs), we employ the spatial Durbin model (SDM) for the subsequent regression analysis, the formula for which is as follows:

$$\begin{gathered} lnMP_{it} = \eta_0 + \rho \sum_j W_{ij} lnMP_{jt} + \eta_1 lnDE_{it} + \eta_2 (lnDE_{it})^2 + \eta_3 lnX_{it} + \eta_4 \sum_j W_{ij} lnDE_{jt} + \\ \eta_5 \sum_j W_{ij} \left(lnDE_{jt}\right)^2 + \eta_6 \sum_j W_{ij} lnX_{jt} + \mu_i + \lambda_t + \varphi_{it} \end{gathered} \quad (3)$$

Here, $lnMP_{it}$ is the logarithm of the MP index for the i-th city in year t; $lnDE_{it}$ is the primary explanatory variable—the DE index; and lnX_{it} includes the chosen control variables. The term ρ signifies the spatial lag coefficient, which measures the influence of MP among neighboring areas; η_0 is the intercept; η_1 to η_3 are coefficients for the explanatory variables; η_4 to η_6 are coefficients for the spatial spillover effects; μ_i accounts for the regional effects; λ_t is the time effect; and φ_{it} is a stochastic error term. The SDM effectively addresses the spatial correlations from various sources and establishes a standard framework for detecting spatial spillovers. Depending on the parameters, the SDM may be transformed into models like the spatial autoregression model (SAR) [30]. In the following, we will conduct various evaluations to pick out the most optimal model setup for our research. To provide a quick overview, we have presented all the test outcomes in Table 4.

Table 4. Correlation tests for model selection.

Test	Content	Statistics	*p*-Value
LM Test	Spatial error	19.276	0.000
	Spatial lag	12.939	0.000
Robust-LM Test	Spatial error	12.199	0.000
	Spatial lag	5.861	0.015
LR Test	SEM and SDM	65.99	0.000
	SAR and SDM	61.75	0.000
Wald Test	SEM and SDM	95.49	0.000
	SAR and SDM	83.02	0.000
LR Test	Two-Way and Spatial	229.16	0.000
	Two-Way and Time	385.93	0.000

We initiate our empirical evaluation with the standard Lagrange multiplier (LM) tests to select the preliminary model. Both the LM and robust LM tests confirm the presence of significant spatial errors and lag effects, as evidenced in Table 4, with all the results notable at a 5% significance level, reinforcing the choice of a spatial econometric model in light of the Moran's I test findings.

Next, likelihood ratio (LR) tests are conducted to compare the different spatial econometric frameworks, including the SDM, SEM, and SAR. The tests indicate that the SDM remains robust, not reducing to the SAR or SEM even at a 1% significance level, which suggests the SDM is suitable as a spatial econometric model. This is consistent with the Wald test outcomes, which align closely with those of the LR tests.

Finally, we perform LR tests to finalize the specifications of the SDM. The results demonstrate that the two-way fixed effects model outperforms both the spatial and temporal fixed effects models at the 1% significance level, leading us to adopt this configuration for our final empirical analysis.

4.2. Empirical Results

Typically, the influence of an explanatory variable on an explained variable is quantified by the partial derivative of the outcome with respect to the explanatory variable. However, in the presence of spatially lagged variables, this relationship becomes more complex, which potentially obscures the traditional measures of impact and significance in spatial econometric models [31]. Instead, LeSage and Pace [32] recommend analyzing the direct, indirect, and total effects to more accurately capture these dynamics in spatial regression models. The direct effect quantifies how much an explanatory variable affects the explained variable locally within the same city, including both the immediate impact and the feedback effect—that is, the influence induced by variables from neighboring regions due to spatial correlations. The indirect effects, often termed spatial spillover effects, reflect how local variables in one city influence the explained variables in other cities. The total effects represent the aggregate of the direct and indirect effects, which essentially describes the overall impact of the explanatory variables on the explained variable across all the cities. Adopting this methodology, we computed the direct, indirect, and total effects within our SDM framework, and the results of these calculations are presented in Table 5.

Table 5. Direct, indirect, and total effects from the SDM regression.

Variables	Direct Effects	Indirect Effects	Total Effects
lnDE	−0.346 **	−2.077 ***	−2.423 ***
	(0.165)	(0.352)	(0.487)
$(lnDE)^2$	−0.0460 *	−0.297 ***	−0.343 ***
	(0.0263)	(0.0570)	(0.0788)
lnUR	0.981 **	2.566 **	3.547 **
	(0.489)	(1.177)	(1.590)
lnEE	−0.0129	0.304	0.292
	(0.0759)	(0.193)	(0.248)
lnPD	0.275 **	0.414	0.688
	(0.128)	(0.330)	(0.435)
lnIS	−0.322	−0.277	−0.599
	(0.261)	(0.613)	(0.809)
lnIO	0.0118	0.00831	0.0201
	(0.0369)	(0.0750)	(0.102)
lnEG	−3.647 ***	−12.21 ***	−15.86 ***
	(1.369)	(3.422)	(4.560)
$(lnEG)^2$	0.187 ***	0.582 ***	0.770 ***
	(0.0631)	(0.157)	(0.209)
lnGI	−0.172	−0.736	−0.908
	(0.187)	(0.438)	(0.584)
lnMED	−0.122	−0.257	−0.379
	(0.131)	(0.276)	(0.358)
Observations	420	420	420
R-squared	0.393	0.393	0.393
Number of id	42	42	42

Note: Figures in () are standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

From the analysis presented in Table 5, we can obtain several key insights:

Firstly, the spatial lag coefficient ρ for marine pollution (MP), represented by W* *lnMP*, registers at 0.674 with statistical significance at the 1% level. This indicates a substantial spatial spillover effect of MP. Such an outcome is anticipated due to environmental dynamics like ocean currents, which naturally facilitate the spread of pollutants from one coastal area to its neighbors. Concurrently, socioeconomic activities, including the shifting of industries and enhanced regional trade, intensify these spatial connections of MP across coastal cities [33]. These interdependencies among marine pollution points in coastal zones underscore the necessity of collaborative and integrated approaches to marine environmental management to effectively address these complex issues [34].

Secondly, as the central explanatory variable in this analysis, the digital economy's development (*lnDE*), demonstrates a substantial suppressive influence on marine pollution (MP) via both direct (5% significance) and indirect (1% significance) effects, culminating in a comprehensive impact significant at the 1% level. The pronounced significance of the indirect effects reveals that the DE exhibits a notable spatial spillover influence; specifically, a 1% enhancement in the DE level leads to a 2.077% reduction in MP in adjacent cities. This finding also aligns with expectations, as the evolution of the DE contributes to more efficient energy usage and the advancement of environmentally friendly technologies, which are crucial for diminishing emissions of marine pollutants [35]. As digital infrastructure and smart technologies evolve, the inter-correlation among cities intensifies, particularly in terms of technological and resource exchanges, which explains the role of local DE enhancements in MP in neighboring urban areas. Additionally, diminishing MP in adjacent regions reciprocally impacts the originating city's emissions, thereby fostering a beneficial cycle of pollution reduction.

Moreover, the regression analysis shows that the quadratic term of the DE ($(lnDE)^2$) exhibits a significantly negative impact, particularly through its indirect effects, suggesting that the DE's influence on MP is distinctly non-linear. When considered alongside the linear term, the relationship between the DE and MP adopts an inverted U-shaped curve, indicating that our analysis falls on the descending side of this curve.

Regarding the control variables, many exhibit no significant impact, a common occurrence in spatial econometric analyses [23,36–38]. Nonetheless, certain variables do demonstrate noteworthy effects on MP. A primary example is urbanization (*lnUR*), which shows a significantly positive correlation with MP, both directly and indirectly, implying that urban growth in a city exacerbates MP locally and in nearby regions. Previous studies, such as the one referenced in Ref. [9], have linked this phenomenon to indiscriminate urbanization efforts by local governments. The increasing population density and land usage intensity in coastal cities lead to environmental strain [39], escalating the self-cleaning burden of coastal waters and consequently heightening marine pollution levels.

Additionally, population density (*lnPD*) emerges as a significant factor, displaying a positive coefficient with a 5% significance level in its direct effects. This correlation is logical, as heightened population density intensifies demand, consumption, and industrial output [40], all of which exacerbate marine pollution. While the positive coefficients for the indirect effects of population density are observed, they do not achieve statistical significance, indicating that the spillover effects of population density on marine pollution are not substantial.

Another pair of significant variables are the economic growth (*lnEG*) and its quadratic term ($(lnEG)^2$). Both variables demonstrate significant impacts at the 1% level across the direct, indirect, and total effects. The analysis shows that economic growth directly correlates with a reduction in marine pollution, whereas the quadratic term exhibits a positive influence. These findings suggest that the relationship between economic growth and marine pollution forms a U-shaped curve, contradicting the traditional environmental Kuznets curve (EKC) hypothesis. This indicates that economic growth and marine pollution have not yet reached a point of disassociation [41].

4.3. Robustness Checks

To verify the impact of the digital economy (DE) on marine pollution (MP), we proceed with several robustness checks. These are essential in spatial econometric analyses where the selection of a spatial weight matrix is critical.

First of all, we substitute the general MP index with the specific pollutant, the inorganic nitrogen, due to its prevalence and impact on water quality in China's coastal regions, as noted in prior research [18]. This pollutant serves as the single benchmark for MP in several studies. Next, we reconstruct the DE index using the TOPSIS method, which offers a comprehensive approach by considering the interplay among the various DE components. Lastly, we switch from the basic binary spatial weight matrix to a more complex matrix based on geometric and economic distances, enhancing the representation of spatial interactions significantly.

The outcomes of the SDM regression for the three robustness tests are presented in Table 6. The findings demonstrate that, consistently across all the tests, the coefficients for the DE and its quadratic term remain negative, consistent with the findings of the earlier analysis. In the first robustness test, where the explained variable is changed, the significance levels for both terms in the direct effects surpass those of the original model. The significance levels in the subsequent tests largely mirror those of the initial regression, with the exception being the quadratic term in the direct effects. These findings reinforce our earlier conclusion that the digital economy contributes to the reduction of marine pollution. Notably, the significance levels for the indirect effects are generally higher than those for the direct effects, mirroring the pattern observed in the benchmark SDM results shown in Table 5, which further confirms the spatial spillover effects of the DE.

Table 6. SDM regression results from robustness checks.

Variables	Replacing Weight Matrix			Replacing Explained Variable			Replacing Core Explanatory Variable		
	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects	Direct Effects	Indirect Effects	Total Effects
lnDE	−0.381 *	−5.645 ***	−6.025 ***	−0.779 ***	−3.448 ***	−4.226 **	−0.443 **	−2.509 ***	−2.951 ***
	(0.205)	(1.460)	(1.608)	(0.251)	(0.644)	(0.868)	(0.213)	(0.454)	(0.630)
$(lnDE)^2$	−0.042	−0.806 **	−0.848 ***	−0.090 **	−0.495 **	−0.585 ***	−0.0559	−0.411 ***	−0.467 ***
	(0.033)	(0.235)	(0.258)	(0.040)	(0.105)	(0.141)	(0.042)	(0.090)	(0.124)

Note: Figures in () are standard errors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5. Conclusions

China's economic expansion and swift urbanization have exposed significant environmental challenges, particularly in the realm of escalating pollution. The marine environment is especially critical within this context, given its essential contribution to human welfare. Concurrently, the rapid growth of the digital economy (DE) has motivated technological innovations and eco-friendly technologies, which have substantially improved both industrial processes and energy consumption patterns, thereby aiding in the reduction of environmental pollutants. While the beneficial impact of the DE on terrestrial and atmospheric environments has been extensively explored, this study—for the first time—extends this examination to the marine context, with the method of spatial econometric models. Utilizing panel data from 42 coastal cities in China, we developed composite indices to quantify the DE and MP and analyzed their relationship using the spatial Durbin model (SDM). The key conclusions of this study are as follows:

(1) There is a pronounced spatial spillover effect among MP in China's coastal cities, whereby an increase in MP in one area tends to precipitate rises in neighboring areas, a phenomenon exacerbated by natural factors such as ocean currents. (2) The DE significantly mitigates MP, with its influence being more pronounced indirectly, reflecting the inherent spatial spillover characteristics of marine ecosystems. (3) The quadratic relationship of the DE indicates a significant non-linear impact on MP, illustrating that the effect of the DE on MP characteristically follows an inverted U-shaped trajectory.

Our study extends the digital economy's environmental benefits to the marine context, which is actually not surprising since digital technology can offer several solutions to existing coastal problems [42]. For instance, enhanced monitoring and management through digital technologies like remote sensing, IoT devices, and data analytics can improve the oversight of coastal environments. These technologies enable real-time data collection and analysis, facilitating better decision-making and rapid responses to environmental issues. Improved waste management is another benefit, where digital platforms optimize waste management systems by enhancing the efficiency of waste collection, sorting, and recycling processes, thereby reducing marine pollution, particularly from plastic waste and other debris. Additionally, the digital economy promotes the adoption of sustainable practices through innovations such as smart grids, precision agriculture, and sustainable supply chains, mitigating the adverse impacts of human activities on coastal ecosystems. Furthermore, digital platforms can increase public awareness and participation in environmental conservation efforts by engaging communities through social media, mobile apps, and online platforms.

6. Discussion

Based on the findings of this research, we propose several policy recommendations. First and foremost, it is crucial for coastal cities to enhance their collaborative efforts in terms of marine conservation and management. Given the widespread nature of marine pollution (MP) and its significant spatial spillover effects, a unified approach to crafting regulations and policies for MP control is essential—isolated efforts by individual local governments will likely prove inadequate. It is important to note that our results indicate that while the digital economy (DE) and green technology play a significant role in managing the spillover or transfer of MP, they do not substantially diminish or control MP at the primary source. Therefore, policies should also focus on addressing the root causes of MP alongside managing its spread. Secondly, it is imperative for local authorities to recognize and support the vital role of the DE in mitigating MP. This support should include, but not be limited to, increased policy incentives for innovative enterprises, greater investment in DE initiatives, and expedited dissemination of digital and green technologies. Lastly, considering the substantial indirect effects of the DE on MP, fostering inter-regional cooperation is critical. This could be facilitated through synchronized efforts in building digital infrastructure like 5G networks that benefit multiple regions. Effective regional collaboration that leverages the strengths of different cities can maximize the potential of the DE to foster a positive cycle of environmental improvement.

It is important to emphasize that because MP is dynamic and complex, effective management involves both temporal and spatial considerations. Our findings underscore the necessity of integrated strategies that address the temporal evolution and spatial distribution of MP to achieve sustainable environmental outcomes.

In this study, we mainly focus on China, while it is beneficial to compare our findings with similar studies conducted in other countries to provide a more global perspective. For instance, research conducted in the United States and Canada has demonstrated the significant role of digital technologies in promoting marine environmental sustainability by understanding and monitoring marine pollution [8]. In Japan, digital advancements have been shown to positively influence marine environmental protection by monitoring microplastic pollution [43]. Similarly, Australia has highlighted the positive influence of digital solutions on environmental protection through better data collection and decisions [44]. These international cases align with our findings, underscoring the potential of the digital economy in driving environmental improvements. Our study contributes to this growing body of literature by providing empirical evidence from China, thereby enriching the global understanding of the interplay between digital development and environmental sustainability.

Our study serves as the first spatial econometric study that explores the DE's impact on MP, although one major limitation is the timeliness of the MP data, which are primarily sourced from the China Coastal Environmental Quality Bulletin. The content of these reports underwent a significant change in 2016. Prior to this, data on four major pollutants were consistently collected; after 2016, the reports included only a subset of these pollutants, and the newer data volume is insufficient for a comprehensive econometric study. For this reason, we restrict ourselves to the data in time range 2006–2015, and we note similar situations also take place in recent studies such as Refs. [19,22]. At this stage, our work serves as exploratory research that focuses on two sets of public datasets (the MP and the DE) whose relation has not been studied before, which is a preliminary effort in this direction. It is imperative to collect newer data to perform a more up-to-date study, where a proper new index should be constructed once the new data volume is sufficient. This will be the direction for a future study.

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Appendix A

The indices and names of the 42 chosen cities, as shown in Figure 1, and the corresponding provinces are listed as below.

City Index	City	Province
1	Dandong	Liaoning
2	Dalian	Liaoning
3	Yingkou	Liaoning
4	Panjin	Liaoning
5	Jinzhou	Liaoning
6	Huludao	Liaoning
7	Qinhuangdao	Heibei
8	Tangshan	Hebei
9	Tianjin	Tianjin
10	Cangzhou	Hebei
11	Dongying	Shandong
12	Weifang	Shandong
13	Qingdao	Shandong
14	Weihai	Shandong
15	Rizhao	Shandong
16	Lianyungang	Jiangsu
17	Yancheng	Jiangsu
18	Nantong	Jiangsu
19	Shanghai	Shanghai
20	Jiaxing	Zhejiang
21	Ningbo	Zhejiang
22	Taizhou	Zhejiang
23	Wenzhou	Zhejiang
24	Ningde	Fujian
25	Fuzhou	Fujian
26	Putian	Fujian
27	Quanzhou	Fujian
28	Xiamen	Fujian
29	Zhangzhou	Fujian
30	Shantou	Guangdong

City Index	City	Province
31	Shanwei	Guangdong
32	Huizhou	Guangdong
33	Shenzhen	Guangdong
34	Zhuhai	Guangdong
35	Jiangmen	Guangdong
36	Yangjiang	Guangdong
37	Maoming	Guangdong
38	Fangchenggang	Guangxi
39	Beihai	Guangxi
40	Zhanjiang	Guangdong
41	Haikou	Hainan
42	Sanya	Hainan

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