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Estimating the Temporal Impacts of Nearshore Fisheries on Coastal Ocean-Sourced Waste Accumulation in South Korea Using Stepwise Regression

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Abstract: Fishing activities have been recognized as one of the primary contributors to marine environmental pollution. Studies have been conducted on the impact of fishing activities on the accumulation of marine debris, but most of these studies have been conducted at specific points in time. This study collected marine debris data over four years in the coastal area of Korea. Data on the magnitude of nearshore fishing activities during the same period were collected and analyzed. Regression models were constructed to explore the impact of nearshore fishing activities on coastal waste accumulation over time. This research aimed to understand the influence of nearshore fishing activities on the accumulation of ocean-sourced coastal waste, leading to the development of a time series regression model. The results indicated that time series models have substantially more explanatory power compared to conventional models, emphasizing the importance of temporal considerations in quantifying the relationship between fishing activities and coastal litter over time.

Keywords: coastal waste accumulation; regression; time series; fishing activity

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1. Introduction

Marine debris (in this study, we use the terms debris, litter, and waste interchangeably to indicate waste found in the oceans and along the shore) has profound and diverse impacts on marine and coastal ecosystems, posing a pervasive threat to biodiversity and ecological balance. Pollutants resulting from marine debris infiltrate the plant system, endangering aquatic life [1,2]. In addition to ecological consequences, it also causes economic losses in fisheries, coastal industries, and tourism [3,4]. The exponential increase in plastic usage since the 1950s has emerged as a primary driver of marine debris, with the discovery of the Great Pacific Garbage Patch in the North Pacific amplifying global attention to the accumulation of plastic waste in the oceans [5].

Research on the generation, accumulation, and movement of marine debris is diverse, and various policies are being implemented globally to reduce marine litter. From the perspective of the sources of marine debris, it is commonly thought that it originates more from land than from the ocean [6]. However, in the case of Korea, it is reported that 65% originates from the sea [3]. Differences observed among countries can be attributed to various factors such as geographical conditions and migration routes. This study aims to investigate and analyze the temporal impacts of nearshore fisheries on coastal ocean-sourced waste accumulation.

In fishing activities, the widespread use of artificial materials such as nets and fishing lines is recognized as one of the primary contributors to marine environmental pollution [7,8]. To address environmental pollution caused by vessels, the International Maritime Organization (IMO) adopted MARPOL as a key international convention in 1973. However, non-compliance with these regulations is frequently observed. For instance, data collected by Australian observers on foreign vessels fishing within the Australian Fishing Zone in 1992 and 1993 indicate that at least one-third of these vessels did not comply with MARPOL regulations [9]. In addition to violations, unintentional waste dumping, such as gear loss and the wear and tear of fishing nets, can significantly contribute to ocean waste generation.

Research on the relationship between fisheries and marine debris has been conducted in various regions and from different perspectives. These studies encompass not only commercial fishing activities [9] but also investigations into the impact of recreational fishing activities [10,11]. Geographically, research has been carried out in diverse locations, including Indonesia [12], the U.S. state of Florida [13], the United Kingdom [14], Brazil [15], the Western Mediterranean Sea [16], and Australia [9,17]. However, most existing studies have been one-time investigations conducted at a specific point in time. This limitation arises from the inability to continuously accumulate data. Since the marine environment is changing dynamically, these one-time surveys do not convey information about changes over time, which can only be overcome by robust sampling at the same site over several years [18].

In this study, to overcome the limitations of one-time studies conducted at specific points in time, we analyzed marine debris data continuously collected over four years in the same coastal area of Korea. Simultaneously, data on nearshore (including coastal area, nearshore means coastal and nearshore area throughout this study) fishing activity during the same period were collected and analyzed. We constructed regression models to explain the impact of nearshore fishing activities on coastal waste accumulation over time.

2. Materials and Methods

2.1. Data Collection

In this study, we use two datasets: (1) plastics which are directly derived from fishing activities in coastal waste monitoring data and (2) nearshore fishing activity data. Coastal waste monitoring data are publicly available through the National Coastal Waste Monitoring Statistical Marine Environmental Information Portal at https://www.meis.go.kr/mli/monitoringInfo/stat.do (accessed on 19 May 2024). Additionally, we obtained nearshore fishing activity data from the National Federation of Fisheries Cooperatives Database, which were essential for our analysis. It is important to note that access to the nearshore fishing activity data is granted by the National Federation of Fisheries under authorization.

2.1.1. Coastal Waste Monitoring Data

Our coastal waste monitoring data embody the meticulous quantification of accumulated coastal waste, providing data points in terms of both weight and quantity. These datasets are the result of a systematic data collection process that has persisted bi-monthly, six times a year, since its inception in 2008. The transition from Monitoring Phase 1 to Monitoring Phase 2 in 2018 marked a significant methodological change. Instead of employing a comprehensive collection strategy along predetermined coastlines, the updated methodology adopts a more statistically refined approach. It involves segmenting each coastline into 20 distinct sections, with each segment spanning 5 m perpendicular to the coastline. For statistical analysis, four of these segments are randomly selected for waste sampling, encompassing both quantity and weight measurements. The selection criteria for monitoring sites are particularly stringent: they must meet conditions such as having a beach length exceeding 100 m, featuring sandy or pebble coastlines, experiencing infrequent cleanup activities, and having the capacity for the complete removal of all coastal waste following monitoring. Initially, 40 monitoring points were established, a number that has since increased to 60, with 20 additional points added to ensure comprehensive coverage [19]. In this study, we rely on Phase II data from 39 monitoring sites out of 60 to ensure data consistency and coherence throughout the study;

the plastic fragments included in this study can be distinguished with the naked eye, although their exact measurements were not recorded.

In the coastal waste monitoring data, plastic waste accounts for the highest proportion, constituting 82.74% of the total quantity and 98% of the total weight. Due to the numerous issues caused by plastic debris, a detailed classification and investigation of this type are being conducted. Table 1 presents a breakdown of plastic waste, along with the total quantity and its proportion over the specified period. In the years 2018 to 2021, fragmentary plastic particles were the most abundant, followed by twisted fishing ropes, beverage bottles, rigid fragments, and styrofoam buoys. The cumulative quantity of litter from the first to the tenth rank accounts for 74.39% of the total litter, indicating that these top ten sub-classifications can explain a significant portion of plastic waste.

Among these plastic sub-classifications, fragmentary plastic particles, twisted fishing ropes, and styrofoam buoys (Ocean-Sourced Waste, OSW) are utilized to construct the designated temporal regression models in this study, as they are believed to be derived solely from ocean activities. It is notable that all these types of ocean-sourced debris rank within the top five in terms of quantity among coastal waste. It is expected that the derived time series regression model will precisely represent the temporal impacts of fisheries on coastal waste accumulation by restricting the resulting debris to OSW, because the factors of the model are clearly limited to ocean-related activities and fishery is considered as one of the major activities that generates ocean debris.

Table 1. Sub-classifications of plastics along with the total quantity and its proportion (2018~2021).

Rank	Category 3	Quantity	Proportion
1	Fragmentary Plastic Particles	14,785	14.03%
2	Twisted Ropes (Fishing)	13,592	12.90%
3	Beverage Bottles and Caps	12,549	11.91%
4	Rigid Plastic Fragments	12,080	11.46%
5	Styrofoam Buoys	6058	5.75%
6	Vinyl Packaging (Ice Cream Wrappers, Snack Bags, etc.)	4838	4.59%
7	Plastic Bags	4588	4.35%
8	Film-type Plastic Fragments	3656	3.47%
9	Cords (Packaging Cords)	3471	3.29%
10	Miscellaneous Rigid Plastic	2780	2.64%
11	Disposable Plates, Spoons, Straws, etc.	2367	2.25%
12	Styrofoam Food Containers (Cup Noodles, Lunch Boxes, Fruit Packaging, etc.)	2165	2.05%
13	Other Fragments	2086	1.98%
14	Other Materials	1919	1.82%
15	Cigarette Butts	1855	1.76%
16	Fake Bait, Fluorescent Hooks, Fishing Bait Containers	1583	1.50%
17	Other Fragmentary Plastic (Sponges, Disposable Wipes, etc.)	1373	1.30%
18	Fiber-type Plastic Fragments	1336	1.27%
19	Fishing Nets	1308	1.24%
20	Synthetic Fiber (Clothing, Synthetic Fabric, Gloves, Socks, Blankets, etc.)	1118	1.06%
21	Plastic Buoys	1099	1.04%
22	Other Plastics	1092	1.04%
23	Styrofoam Packaging Cushioning Material (Shock Absorbers for Electrical Appliances, etc.)	1085	1.03%
24	Food Packaging Containers (Red Pepper Paste Tubes, Soy Sauce Bottles, etc.)	756	0.72%
25	Lighters	741	0.70%
26	Fireworks and Firework Accessories	636	0.60%
27	Styrofoam Fishing Boxes	596	0.57%
28	Fishing Lines	566	0.54%
29	Film-type Plastics (Disposable Hygienic Gloves, etc.)	417	0.40%
30	Toys, Dolls, Recreational Items, Office Supplies	402	0.38%
31	Detergent Containers	396	0.38%
32	Trap and Eel Trap Bait Containers	373	0.35%
33	Fiber-type Plastics (Nets, Packaging Materials, etc.)	365	0.35%
34	Packaging Bands (Wide, Hard Bands)	234	0.22%
35	Pesticide Containers and Insecticides	187	0.18%
36	Syringes	146	0.14%
37	Various Vinyl Packaging	135	0.13%
38	Buoys (Black)	100	0.09%
39	Aquaculture Chemical Containers	97	0.09%
40	Film-type Balloons	96	0.09%

Table 1. *Cont.*

Rank	Category 3	Quantity	Proportion
41	Various Styrofoam	86	0.08%
42	Buoys (Round Bar, Large, Blue)	83	0.08%
43	Buoys (Bar, Orange)	72	0.07%
44	Medicine Bottles and Packaging, Syringes, etc.	40	0.04%
45	Miscellaneous Rigid Buoys	39	0.04%
46	Buoys (Oval, Blue)	36	0.03%

2.1.2. Nearshore Fishing Activity Data

Data on nearshore fishing activity spanning from 2018 to 2021 have been comprehensively compiled, comprising five primary categories with a total of 54 sub-categories. Each sub-category has been detailed with the corresponding number of fishing trips and the average catch per trip, as presented in Table 2, which illustrates the results of this statistical inquiry. It should be noticed that all fishery data collected represent the summation of fishing activities conducted within a 30 km radius of each monitoring site.

Figure 1 depicts the total fishing trips and average catch by major fishing method category. The bar chart represents the overall fishing trips, while the line chart represents the average catch. The fishing trips are indicated on the left vertical axis, and the average catch is shown on the right vertical axis. Net fishing records the highest total number of fishing trips and the greatest average catch, whereas aquaculture exhibits the lowest total fishing trips, and combo fishing demonstrates the lowest average catch. Despite their higher number of fishing trips, the combo fishing and fishing methods exhibit notably lower average catch values in comparison to other fishing techniques.

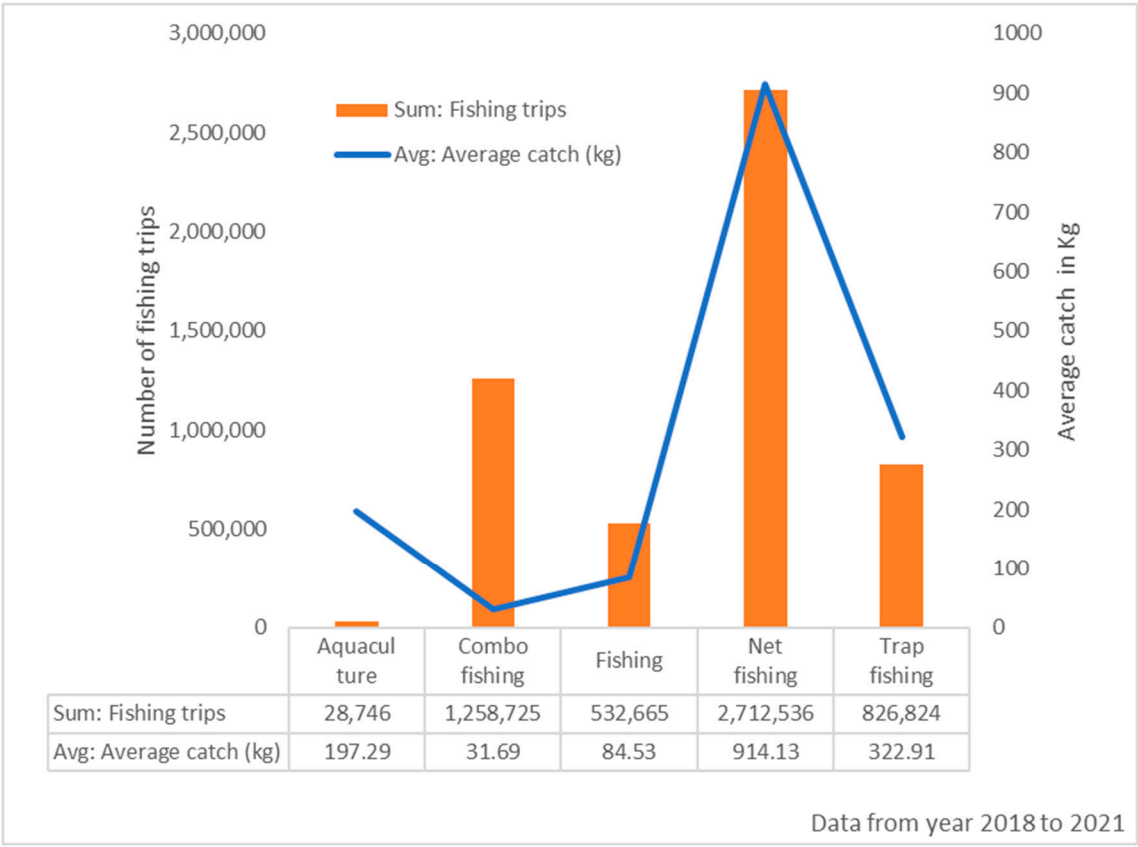


Figure 1. Total fishing trips (bar) and average catch (line) by major fishing method category.

Table 2. Total fishing trips and average catch by fishing method from 2018 to 2021.

Major Category	Sub-Category	Fishing Trips	Average Catch (kg/trip)
Aquaculture	Coastal Cage Farming	6192	15.21
	Aquaculture	22	15
	Inland Tanks Aquaculture	7	7.86
	Inland Embankment Aquaculture	12	1120
	Cooperative Aquaculture	363	10.24
	Bottom Surface Aquaculture	14,070	59.44
	Hanging Aquaculture	7359	214.26
	Mixed Aquaculture	721	136.33
Combo Fishing	Coastal Combo Fishing	1,258,725	31.69
Fishing	Offshore Longline Fishing	179,454	200.51
	Offshore Single-line Fishing	292	132.99
	Fishing Vessels	187,794	22.44
	Fishing	657	15.42
	Coastal Single-line Fishing	1	5
	Jig Fishing	164,467	130.8
Net Fishing	Fish Fence Fishing	3902	65.59
	Anchovy Trawl Fishing	72,313	921.97
	Village Net Fishing	8555	33.97
	Offshore Stick-held Dip Net Fishing	472	229.34
	Large Purse Seines Fishery	14,887	27,372.52
	Small Purse Seines Fishery	11,696	290.34
	Coastal Seines Fishery	30,273	179.18
	Fyke Net Fishing	3296	28.35
	Funnel Net-type Fishing	7148	26.45
	Stow Net Fishing	191,476	259.31
	Coastal Improved Stow Net Fishing	182,626	71.48
	Coastal Stow Net Fishing	209	39.05
	Offshore Fixed Gill Net Fishing	22,778	177.52
	Offshore Drift Gill Net Fishing	81,273	203.36
	Offshore Gill Net Fishing	174,209	251.76
	Coastal Drift Gill Net Fishing	772	46.71
	Coastal Gill Net Fishing	1,626,838	44.62
	Winged Gape Net Fishing	17,428	29.06
	Long Bag Net-type Fishing	607	23.49
	Long Bag Net Fishing	26,771	13.95
	Gape Net Fishing	10,353	20.38
	Large Trawl Fishing	467	1501.51
	Eastern Sea Medium Single Trawl Fishing	17,679	226
	South-western Sea Medium Double Trawl Fishing	14,201	707.08
	South-western Sea Medium Single Trawl Fishing	43,913	188.34
	Large Double Seine Fishing	39,644	1271.27
	Large Single Seine Fishing	47,363	197.25
	Large Set Net Fishing	4188	80.76
	Small Set Net Fishing	278	15.4
	Set Net Fishing	204	34.51
	Medium Set Net Fishing	1194	261.9
	Large Trawl Fishing	19,080	543.69
	Eastern Sea Medium Trawl Fishing	3461	683.51
	Offshore Dredge Fishing	29,952	197.9
	Shellfish Dredge Fishing	3030	144.67
Trap Fishing	Offshore Eel Trap Fishing	57,988	420.18
	Offshore Trap Fishing	106,477	820.51
	Coastal Trap Fishing	662,358	40.94
	Trap Fishing	1	10

2.2. Method

2.2.1. Clustering Analysis

Although the statistical model incorporates a large amount of data from all coastal waste monitoring sites, it may be less significant. This is due to reduced data homogeneity caused by regional disparities. To mitigate these issues, this study seeks to categorize regions according to coastal litter characteristics and develop region-specific statistical models using monitoring data from regions that share similar attributes. Clustering analysis was employed to identify groups of waste with similar attributes or to form regional groups of waste exposure, as demonstrated in previous studies on ocean pollution [20,21].

To cluster the designated monitoring sites, we employed the K-means clustering method, one of the renowned techniques for data clustering, and applied the various algorithms to determine the most suitable number of clusters. We contend that employing cluster analysis to categorize coastal litter monitoring sites according to their litter gen-

eration characteristics will assist in developing customized models that account for the distinctive traits of each region.

The coastal waste monitoring data under consideration were collected from 39 monitoring points over the period of 2018 to 2021. These data were gathered at a rate of 60 distinct sub-classification data per waste collection for each monitoring site, conducted 24 times over the course of four years. Consequently, each monitoring site has a total of $60 \times 24 = 1440$ coastal waste data. To represent each monitoring point as a single row vector and facilitate cluster analysis, the data from each monitoring point were organized into clusters. It is worthy to note that the complete dataset consists of 39 rows and 1440 columns with each row corresponding to a coastal waste monitoring site.

To determine the optimal number of clusters for data clustering, we utilized the NbClust package within the R programming environment [22]. This package offers a selection of 12 distinct algorithms for cluster number determination, and we opted for the cluster count recommended by the majority of these algorithms. Subsequently, we applied the K-means clustering method for our analysis.

2.2.2. Stepwise Regression Considering Temporal Impacts

After the clustering analysis for the coastal waste monitoring data, stepwise regression models were employed to seek the appropriate regression model for each cluster of the monitoring sites. Specific types of marine litter monitoring data, OSW, such as fishing ropes and styrofoam buoys, are known to be the result of fishing activities. By treating data linked to marine litter presumed to be induced by fisheries activity as the dependent variable and fisheries activity data as the independent variable, we can leverage their well-established causal relationship for statistical modeling. Thus, we aim to quantify the influence between them.

To account for the temporal disparity in marine litter generation and accumulation, we seek to enhance the model's fitness through time series data modeling. According to our literature survey, no previous studies consider the time series model to explain coastal waste accumulation. The regional model for fisheries-induced marine litter introduced in this study is expected to form the basis for developing a more comprehensive model that encompasses socioeconomic factors in the future.

Conventional single-variable time series analysis typically employs autoregressive models (AR) to establish models that explain the data using a variable's own historical data. In contrast, multivariate time series analysis, such as vector autoregressive models (VAR), employs techniques to create models that explain data from multiple time series, including the variable itself.

In this study, we propose a model using a temporal approach where independent variables include past fisheries activity data, and factor selection is achieved through stepwise regression analysis. Given that our analysis involves both marine litter monitoring data and time series data collected from fisheries activities, it appears that a VAR-type analysis is warranted. Nevertheless, the relatively short data collection period of 24 time points (6 times per year for 4 years) for marine litter monitoring data in comparison to the number of independent variables (8) selected may limit the applicability of VAR analysis. It is recommended to use a time series stepwise regression model when the length of the available time series data is relatively short compared to the number of independent variables in the implemented model [23]. Additionally, marine litter monitoring data are collected simultaneously with its removal, theoretically preventing the litter itself from serving as an independent variable that explains litter accumulation, in addition to other factors. Consequently, we conclude that directly applying traditional time series analysis methods may not be appropriate.

Although the application of the stepwise regression model for time series data cannot be found in the prediction of coastal waste management, studies have been conducted on other research areas to predict water consumption and national GDP growth [23–25].

To demonstrate the temporal nature of marine litter generation and accumulation, we initially present a regression model that does not account for time series data. Subsequently,

we propose a time series model, and the R-square value of these two models is compared. Both models employ stepwise regression analysis. The dependent variables include the summation data of expanded particles, fishing ropes, styrofoam buoys, fishing lines, and nets attributed to fisheries-induced litter. The independent variables consist of the average catch (kg per trip) and the number of fishing trips for net fishing, line fishing, aquaculture, and combo fishing. It should be noted that trap fishing was omitted from the independent variables, primarily due to the infrequent occurrence of marine litter associated with trap fishing at the coastal waste monitoring sites. Table 3 presents the variable names used in the regression analysis.

Table 3. Variables for the regression model and their description.

Variables	Description
y	Total fishing activity-induced coastal waste
n_avg	Average catch per trip for net fishing
n_cnt	Number of net fishing trips
f_avg	Average catch per trip for hook and line fishing
f_cnt	Number of hook and line fishing trips
a_avg	Average catch per trip for aquaculture
a_cnt	Number of aquaculture trips
c_avg	Average catch per trip for combo fishing
c_cnt	Number of combo fishing trips

We describe the simple regression model and the time series regression model, respectively, as:

$$y \sim n_avg_0 + n_cnt_0 + f_avg_0 + f_cnt_0 + a_avg_0 + a_cnt_0 + c_avg_0 + c_cnt_0 \quad (1)$$

$$y \sim \sum_{i=0}^{5} \{n_avg_i + n_cnt_i + f_avg_i + f_cnt_i + a_avg_i + a_cnt_i + c_avg_i + c_cnt_i\} \quad (2)$$

Equations (1) and (2) describe the simple regression model and the time series regression model, respectively. In these equations, the subscript indices signify the time lag between dependent and independent variables. For instance, the subscript value 0 in n_avg_0 denotes the average catches of net fishing at the same time as the measurement of the y value, whereas the subscript value 1 implies that the value was measured 2 months earlier than the y value. It is worth mentioning that stepwise regression was employed in both models, resulting in the inclusion of a subset of independent variables in the final regression models.

In this context, the term "time period" represents the lag interval between coastal litter observation and the corresponding fishing activities. For instance, when examining litter observed in December, time period 0 corresponds to fishing activities in November and December, time period 1 pertains to fishing activities occurring in September and October, and time period 5 relates to fishing activities in January and February.

After the stepwise regression models were implemented, the relative importance of each factor in the temporal regression models is examined to ascertain the contribution of individual fishing activities within specific time periods. Relative importance signifies the impact of a factor in a regression model on the R-square value of the model. In this study, the assessment of relative importance utilizes the "relaimpo" R package, incorporating six metrics for this computation: lmg, pmvd, last, first, betasq, and pratt [26]. Among these metrics, lmg is employed to determine the average contribution of each fishing activity to the R-square value, representing the explanatory power of the established regression model. The impact of a specific fishing activity is estimated as the sum of the relative importance of individual factors.

3. Results

3.1. Coastal Waste Monitoring Data Clustering Result

The cluster analysis was carried out separately for both quantity and weight data, and we selected the clustering results that demonstrated the best performance for further examination. Coastal monitoring sites were grouped into four clusters using quantity data, while six clusters were identified when using weight data. The results from the weight data analysis appeared to produce more balanced groups compared to the quantity data, leading us to select the clustering results that identified six distinct groups of coastal monitoring sites for our study. All the coastal waste monitoring sites appear as circles with the corresponding cluster distinguished by the color in Figure 2.

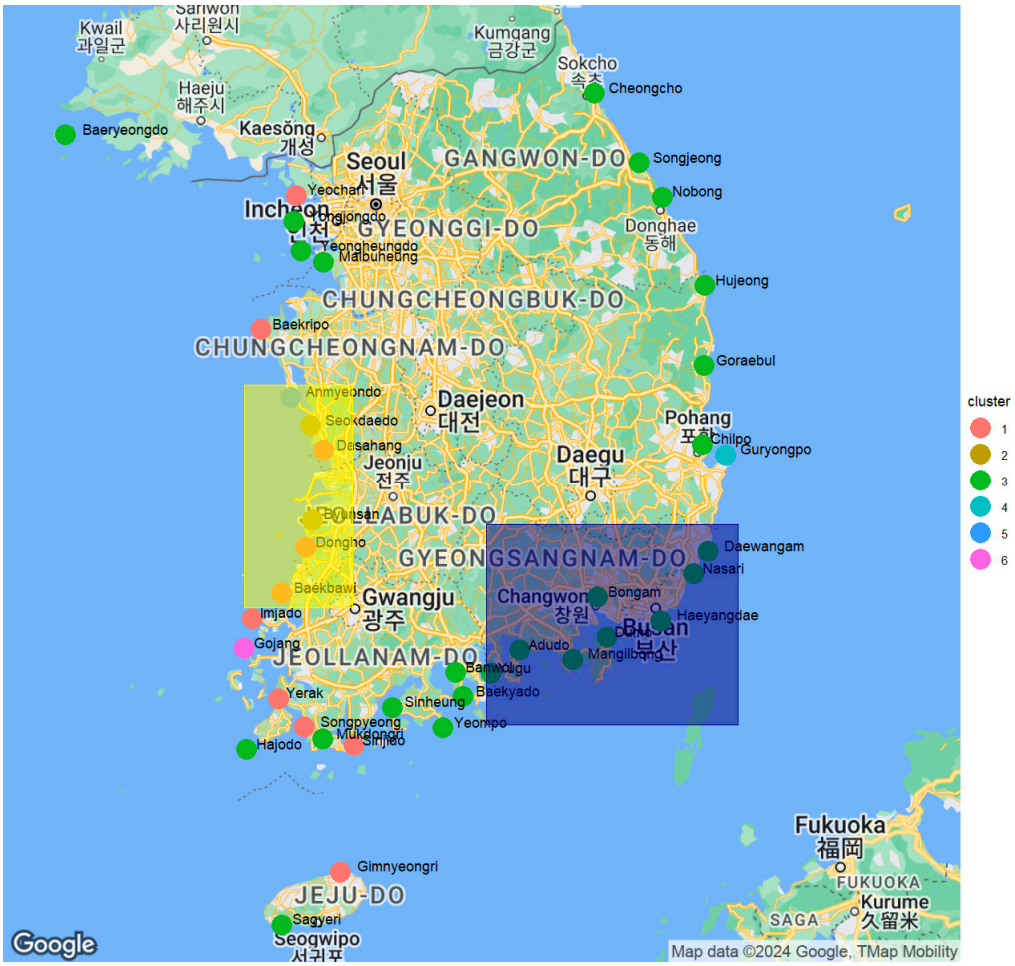


Figure 2. Clustering results.

3.2. Regression Models

From the clusters identified in Section 3.1, we chose clusters 1 and 3 as the focal groups for constructing regression models. This selection was based on these two clusters having the highest number of monitoring sites. For the development of regression models, a subset of monitoring sites from the selected focal groups was included. Specifically, we chose six sites from cluster 1, 2 and 5, which are situated in the south-western region (the yellow box in Figure 2), and seven sites from cluster 3, located in the south-eastern area (the blue box in Figure 2).

3.2.1. Regression Models for South-Western Region

The coastal monitoring sites selected for analysis in the southwest sea area are six in total. Sites not clustered with cluster 1 were included due to their close geographical proximity, ensuring a sufficient number of data points.

Table 4 represents the results of the conventional model that is a regression model, not considering the temporal delay of the litter originating from fishing activities. Average catch of combined fishing, net fishing trips, fishing trips, aquaculture trips, and combined fishing trips were selected as significant variables. Except for the combined fishing trips, the coefficients of the other variables were negative, indicating a negative correlation between fishing activities and coastal waste. A backward elimination strategy was employed in the stepwise regression analysis, with a significance level set at 0.2. It is worthy to note that the significance level for the stepwise regression model is less stringent than that of the full regression model in which 0.05 is used as the significance level. The recommended significance level for stepwise regression ranges from 0.15 to 0.4 [27–29]. The model's R-square value was found to be very low at 0.168.

Table 4. Conventional model for south-western region.

Variable	Coefficient	Standard Error	*t*-Value	Pr(>|t|)
Constant	2.01837	0.43526	4.637	1.05×10^{-5}
c_avg_0	−4.00705	2.67794	−1.496	0.1377
n_cnt_0	−0.06205	0.03367	−1.843	0.0683
f_cnt_0	−0.46605	0.19337	−2.41	0.0177
a_cnt_0	−0.05613	0.03452	−1.626	0.1071
c_cnt_0	0.19638	0.08085	2.429	0.0169
R-squared		0.1676		
Adjusted R-squared		0.1268		

Table 5 presents the results of the time series regression model in the southwest sea area. The R-square value of 0.544 indicates a significant improvement compared to the general regression analysis. The adjusted R-square (adj-R-square) value accounts for the number of independent variables, preventing an artificial increase in the R-square value as the number of independent variables rises. The adj-R-square value of 0.4326 shows a slight decrease compared to the R-square value, but it remains above 0.4. This indicates that the model is still valid considering the number of independent variables.

Variable selection across different time lags revealed that variables of the 2nd and 3rd lags had the highest representation, each with five independent variables. The relative importance showed that the 4th lag variable, c_cnt_4 (representing the number of combo fishing trips), had the highest importance at 12.7%, while the 0th lag variable, f_avg_0 (indicating the average catch in line fishing), had the lowest relative importance at 1.1%.

Table 5. Time series model for south-western region.

Variable	Coefficient	Standard Error	*t*-Value	Pr (>|t|)
Constant	1.54244	0.70146	2.199	3.06×10^{-2}
f_avg_0	3.60321	1.67136	2.156	0.033887
f_cnt_0	1.09048	0.35482	3.073	0.002835
c_cnt_0	−0.20683	0.057	−3.628	0.000483
c_avg_1	−14.2267	3.60502	−3.946	0.000162
f_cnt_1	−0.86617	0.31472	−2.752	0.007219
f_avg_2	6.4558	1.71564	3.763	0.000306
a_avg_2	−0.13617	0.08158	−1.669	0.098727
f_cnt_2	−0.99735	0.40359	−2.471	0.015438
a_cnt_2	−0.05832	0.02823	−2.066	0.04185

Table 5. *Cont.*

Variable	Coefficient	Standard Error	*t*-Value	Pr (>|t|)
c_cnt_2	0.37377	0.09246	4.043	0.000115
n_avg_3	−5.36948	1.39558	−3.847	0.000229
f_avg_3	2.66226	1.73349	1.536	0.128264
a_avg_3	−0.17988	0.08662	−2.077	0.040817
f_cnt_3	0.9043	0.36743	2.461	0.015848
c_cnt_3	−0.39833	0.08913	−4.469	2.38×10^{-5}
f_avg_4	3.4314	1.62741	2.109	0.037896
n_cnt_4	−0.36898	0.07079	−5.213	1.26×10^{-6}
c_cnt_4	0.90432	0.16284	5.554	3.07×10^{-7}
c_avg_5	−5.63903	3.5253	−1.6	1.13×10^{-1}
n_cnt_5	0.07798	0.04436	1.758	8.23×10^{-2}
a_cnt_5	−0.07323	0.0317	−2.31	2.33×10^{-2}
R-squared		0.544		
Adjusted R-squared		0.4326		

The importance of each variable in the regression models that account for lag data, as described in Figure 3, is summarized by fishing method and time period in Tables 6 and 7.

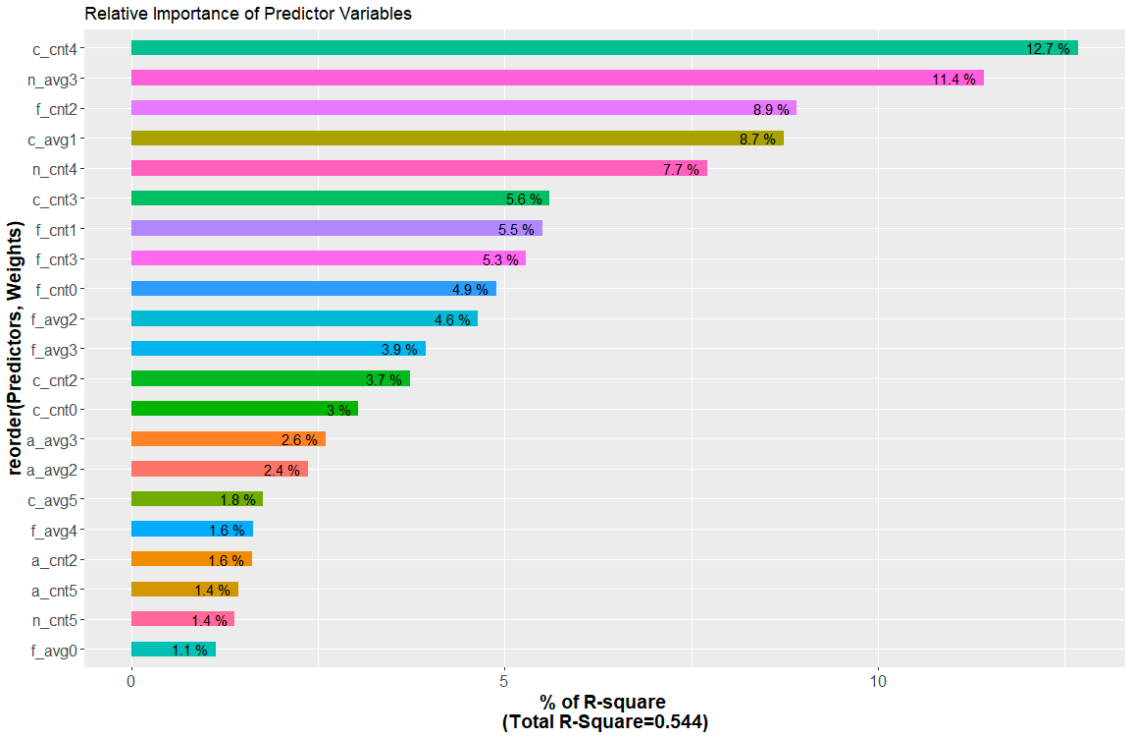


Figure 3. Relative importance for south-western time series regression model.

Table 6 demonstrates that combo fishing and fishing with fishing lines exert the most substantial influence on the accumulation of coastal litter in the southwest sea area. The collective impact of these two fishing methods explains over 70% of the observed variance, while net fishing contributes approximately 20.5%, and aquaculture makes up the remaining 8% of the overall influence. Notably, aquaculture exhibits a relatively modest influence in the southwest sea area.

Temporal dynamics are detailed in Table 7. Among different temporal intervals for fishing activities, time period 3 (occurring 6 months earlier) exerts the most pronounced influence, accounting for approximately 28%, while time periods 2 (4 months earlier) and 4 (8 months earlier) each demonstrate an impact of around 22%.

Table 6. Relative impact on coastal waste accumulation by fishing method in south-western region.

Fishing Method	Variables	Relative Importance	Sub-Total
Aquaculture	a_avg_2	2.4	8
	a_avg_3	2.6	
	a_cnt_2	1.6	
	a_cnt_5	1.4	
Combo Fishing	c_avg_1	8.7	35.5
	c_avg_5	1.8	
	c_cnt_0	3	
	c_cnt_2	3.7	
	c_cnt_3	5.6	
	c_cnt_4	12.7	
Fishing	f_avg_0	1.1	35.8
	f_avg_2	4.6	
	f_avg_3	3.9	
	f_avg_4	1.6	
	f_cnt_0	4.9	
	f_cnt_1	5.5	
	f_cnt_2	8.9	
	f_cnt_3	5.3	
Net Fishing	n_avg_3	11.4	20.5
	n_cnt_4	7.7	
	n_cnt_5	1.4	

Table 7. Relative impact on coastal waste accumulation by time lag in south-western region.

Time Period	Variables	Relative Importance	Sub-Total
0 (no time difference)	c_cnt_0	3	9
	f_avg_0	1.1	
	f_cnt_0	4.9	
1 (two months earlier)	c_avg_1	8.7	14.2
	f_cnt_1	5.5	
2 (four months earlier)	a_avg_2	2.4	21.2
	a_cnt_2	1.6	
	c_cnt_2	3.7	
	f_avg_2	4.6	
	f_cnt_2	8.9	
3 (six months earlier)	a_avg_3	2.6	28.8
	c_cnt_3	5.6	
	f_avg_3	3.9	
	f_cnt_3	5.3	
	n_avg_3	11.4	
4 (eight months earlier)	c_cnt_4	12.7	22
	f_avg_4	1.6	
	n_cnt_4	7.7	
5 (ten months earlier)	a_cnt_5	1.4	4.6
	c_avg_5	1.8	
	n_cnt_5	1.4	

3.2.2. Regression Models for the South-Eastern Region

The coastal monitoring sites selected for analysis in the south-eastern sea are seven in total, classified in the same cluster according to the cluster analysis results (Figure 2).

Table 8 presents the results of the conventional model for the south-eastern sea area. Significant variables selected include the average catch of fishing line fishing, the average

catch of aquaculture, and the average catch of combo fishing. However, the R-squared value is notably low, at 0.078.

Table 8. Conventional model for south-eastern region.

Variable	Coefficient	Standard Error	*t*-Value	Pr(>|t|)
Constant	2.74823	0.51673	5.319	4.81×10^{-7}
f_avg_0	2.16237	1.417	1.526	0.1296
a_avg_0	−0.15551	1.06117	−2.542	0.0123
c_avg_0	−4.11147	2.05385	−2.002	0.0475
R-squared		0.07815		
Adjusted R-squared		0.05548		

Similar to the outcomes from the time series regression model in the south-western region, the south-eastern area also demonstrates a notably higher R-squared value than that achieved by the simple regression model. Table 9 showcases an R-squared value of 0.5105 for the south-eastern region, indicating significantly enhanced explanatory capability compared to simple regression analysis. The adj-R-square value of 0.4059 shows that the model is still valid concerning the number of independent variables.

Among the lag variables, both the 1st and 3rd lags have the highest influence on coastal waste accumulation in the south-eastern region, each featuring five variables. When assessing relative importance, it becomes evident that aquaculture activities with a lag of five time periods carry the greatest significance at 12.1%, while the 3rd lag in combo fishing's average catch exhibits the lowest importance at 1.2%, as the results shown in Figure 4.

Table 9. The time series regression model for the south-eastern region.

Variable	Coefficient	Standard Error	*t*-Value	Pr(>|t|)
Constant	16.35444	6.75476	2.421	1.72×10^{-2}
n_avg_0	3.9317	2.31056	1.702	0.091843
a_avg_0	−0.13713	0.08315	−1.648	0.102168
a_cnt_0	0.44985	0.14135	3.182	0.001931
n_avg_1	14.62571	4.56619	3.203	0.00181
c_avg_1	−6.92424	2.23576	−3.097	0.002519
n_cnt_1	−0.01673	0.01187	−1.41	0.161514
a_cnt_1	−0.34899	0.11884	−2.937	0.004092
c_cnt_1	0.8321	0.27576	3.018	0.003211
n_avg_2	−6.5311	4.09674	−1.594	0.113951
f_avg_2	−3.39125	1.84694	−1.836	0.069221
c_avg_3	3.79867	2.90096	1.309	0.193295
n_cnt_3	0.02487	0.01502	1.656	0.100844
f_cnt_3	2.42366	1.7821	1.36	0.176797
a_cnt_3	−0.19956	0.10653	−1.873	0.63852
c_cnt_3	−0.54821	0.15758	−3.479	0.000739
n_avg_4	10.46709	4.20227	2.491	0.014343
f_avg_4	3.1383	2.00603	1.564	0.120784
a_avg_4	−0.11951	0.06563	−1.821	0.071519
c_avg_4	−13.53992	4.62505	−2.928	0.004206
a_avg_5	−0.17262	0.07571	−2.28	0.024674
f_cnt_5	4.91696	1.84864	2.66	0.00907
a_cnt_5	−0.21667	0.12104	−1.79	0.076386
R-squared		0.5105		
Adjusted R-squared		0.4059		

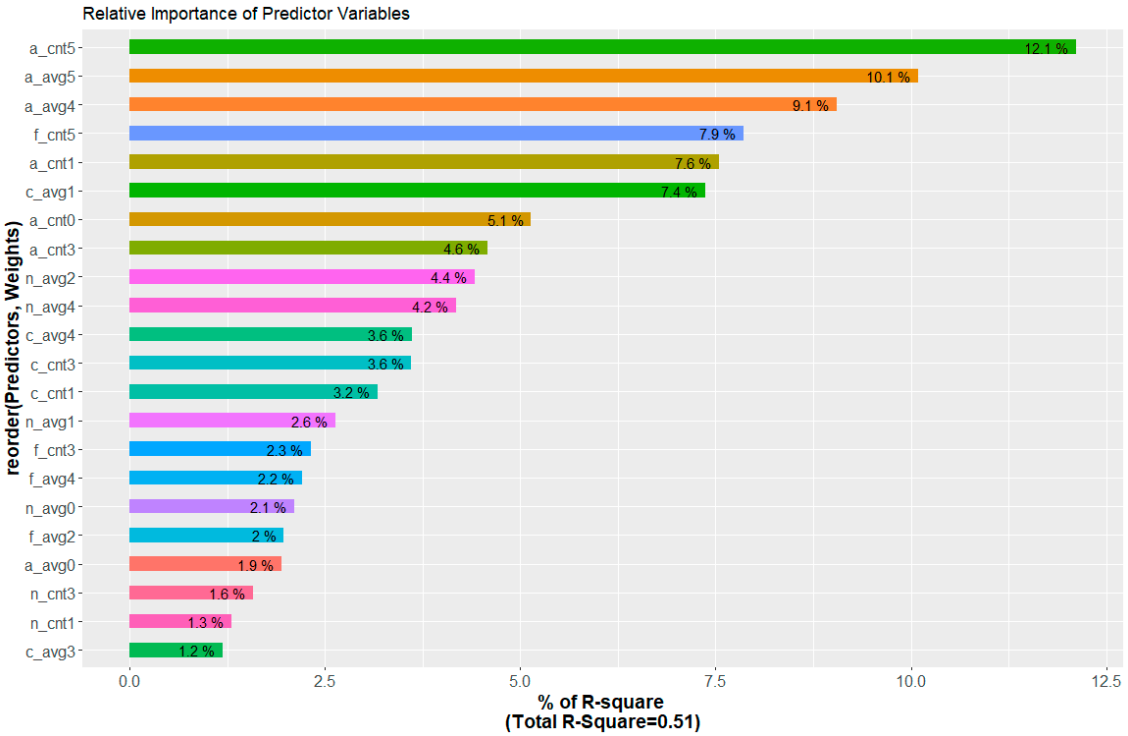


Figure 4. Relative importance for south-eastern time series regression model.

As in the case of the south-western region, this study also evaluates the importance of the regression models developed for the south-eastern area. The significance of these models is summarized with regard to fishing activities and temporal effects in Tables 10 and 11, respectively.

Table 10. Relative impact on coastal waste accumulation by fishing method in south-eastern region.

Fishing Method	Variables	Relative Importance	Sub-Total
Aquaculture	a_avg_0	1.9	50.5
	a_avg_4	9.1	
	a_avg_5	10.1	
	a_cnt_0	5.1	
	a_cnt_1	7.6	
	a_cnt_3	4.6	
	a_cnt_5	12.1	
Combo Fishing	c_avg_1	7.4	19
	c_avg_3	1.2	
	c_avg_4	3.6	
	c_cnt_1	3.2	
	c_cnt_3	3.6	
Fishing	f_avg_2	2	14.4
	f_avg_4	2.2	
	f_cnt_3	2.3	
	f_cnt_5	7.9	
Net Fishing	n_avg_0	2.1	16.2
	n_avg_1	2.6	
	n_avg_2	4.4	
	n_avg_4	4.2	
	n_cnt_1	1.3	
	n_cnt_3	1.6	

Table 11. Relative impact on coastal waste accumulation by time lag in south-eastern region.

Time Period	Variables	Relative Importance	Sub-Total
0 (no time difference)	a_avg_0	1.9	9.1
	a_cnt_0	5.1	
	n_avg_0	2.1	
1 (two months earlier)	a_cnt_1	7.6	22.1
	c_avg_1	7.4	
	c_cnt_1	3.2	
	n_avg_1	2.6	
	n_cnt_1	1.3	
2 (four months earlier)	f_avg_2	2	6.4
	n_avg_2	4.4	
3 (six months earlier)	a_cnt_3	4.6	13.3
	c_avg_3	1.2	
	c_cnt_3	3.6	
	f_cnt_3	2.3	
	n_cnt_3	1.6	
4 (eight months earlier)	a_avg_4	9.1	19.1
	c_avg_4	3.6	
	f_avg_4	2.2	
	n_avg_4	4.2	
5 (ten months earlier)	a_avg_5	10.1	30.1
	a_cnt_5	12.1	
	f_cnt_5	7.9	

Table 10 highlights that, within the context of coastal litter accumulation in the south-eastern region, aquaculture activities emerge as the dominant driving force. Aquaculture's influence stands out prominently, accounting for approximately 50%, surpassing the impact of other fishing activities by a substantial margin. This heightened influence can be attributed to the prevalence of numerous closely situated, small-scale aquaculture operations in the region.

Temporal influences in the south-eastern region are presented in Table 11. Among the temporal factors associated with fishing activities, it is evident that time lag 1 (2 months prior) and time lag 5 (10 months prior) exhibit substantial influence, contributing 22% and 30%, respectively. In cumulative terms, these two periods account for over 50% of the impact. On the other hand, the remaining time periods do not exceed 10%, with time periods 0 and 2 registering at 9.1% and 6.4%, respectively. In contrast, time periods 3 and 4 surpass 10%, with values of 13.3% and 19.1%, respectively, though their impact remains lower than that of time period 5. This pattern may be attributed to the south-eastern region being characterized by a more intricate coastline in comparison to the south-western region. This complexity, occasionally obscured by islands, can result in fishing activity effects manifesting more promptly or with some delay.

3.3. Model Validation

Pairwise T-tests were conducted to assess the model's validation. As previously mentioned, the time series data collected were insufficient to divide into training and test groups. Therefore, data collected from different sites clustered within the same group were used to validate the models. For the south-western region, four sites clustered as cluster 1 were utilized, and for the south-eastern region, five sites clustered as cluster 3 were used to test the validity of the regression models. Table 12 indicates that there is no statistical difference between the proposed model's predictions and the actual observed data.

Table 12. T-test results.

South-Western Region			South-Eastern Region		
Mean of x	***t*-Value**	***p*-Value**	**Mean of x**	***t*-Value**	***p*-Value**
1.27×10^{-15}	7.86×10^{-16}	1	1.33×10^{-16}	6.57×10^{-16}	1

Figure 5 presents the quantile–quantile (QQ) plot results for the proposed time series regression models. Although some outliers were found in the tails, most of the data align closely with the diagonal line.

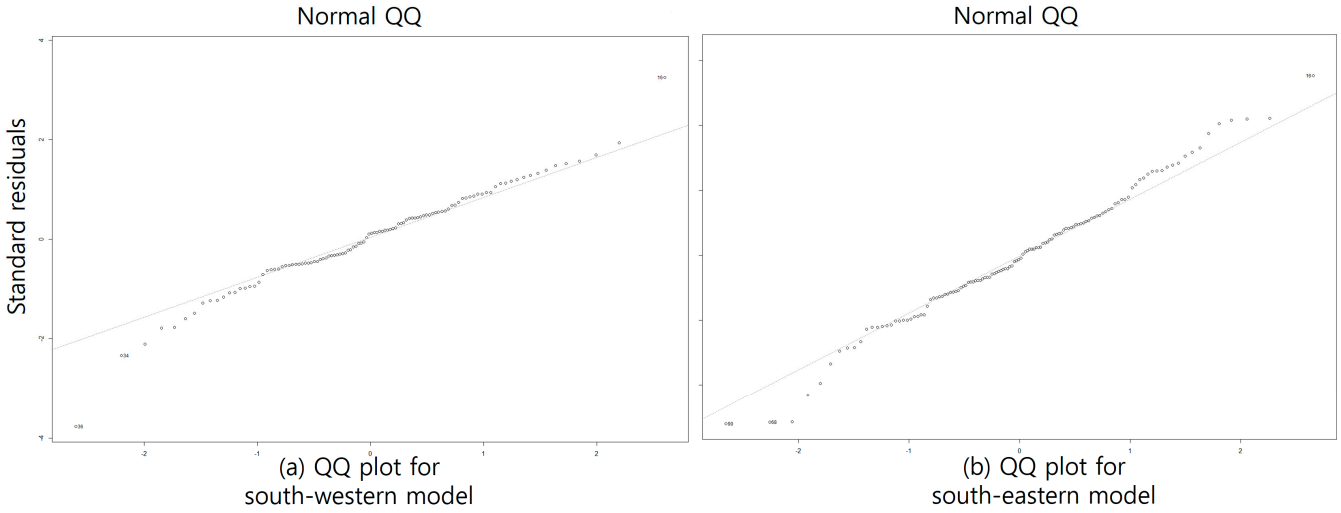


Figure 5. QQ plots for the proposed time series models.

4. Discussion

Based on the results outlined in Section 3, it can be inferred that a correlation exists between coastal waste accumulation, likely originating from ocean-related activities, and fishing practices. The implemented time series regression models for both the south-western and south-eastern regions of South Korea elucidate more than 50% of coastal debris accumulation from ocean sources, whereas models that neglect temporal effects can account for just over 10% of the accumulation. The R-square values slightly exceeding 0.5 in the temporal regression models might appear insufficient to demonstrate the adequacy of the models in depicting the impact of nearshore fishing activities on coastal waste accumulation. However, in social science, an R-square value of 0.5 is acceptable to show the model's fitness to the actual data, when most independent variables are statistically significant. This is particularly relevant as social science studies consider the impact of human behavior, characterized by vast variance, on a specific subject [30]. In this context, it can be concluded that the proposed temporal regression models have sufficiently high R-square values to illustrate the relative effect of fishing activities on the accumulation of coastal waste.

In this research, we introduce time series regression models designed to incorporate the influence of nearshore fishing activities on the temporal accumulation of coastal waste. The existing literature has offered a limited number of studies proposing numerical models to quantify the influence of human activities on ocean waste accumulation [3,31–34]. While it is evident that human activities take time to manifest as actual waste accumulation, none of the preceding studies, according to our literature survey, delve into the temporal impact of human activities on ocean waste accumulation. However, our proposed models offer the ability to point out the fishing method, quantity, and timing of nearshore fishing activities that influence coastal litter accumulation during specific time periods. In our model for the south-western region, the average quantity of fishing line with a lag of 4 exhibits

a relative impact of approximately 1.6% on the current accumulation of coastal waste, whereas that with a lag of 0 demonstrates a 1.1% impact. This allows for a discernment of both the magnitude of the influence of fishing line and the timing of its impact on coastal litter. Knowing the magnitude and time of a fishing activity's impact on the coastal litter accumulation will let the administration in charge of the coastal litter obtain insights to manage the fishing activity to avoid litter accumulation on the coast.

The proposed time series regression models indicate that there is a temporal delay before the impact of fishing activities translates into actual coastal litter accumulation. In the south-western region model, fishing activities with time lags 2, 3, and 4 collectively contribute to over 70% of the model's explanatory power, while those with time lags 1 and 5 account for over 50% in the south-eastern region model. The timing of fishing activities appears to have a relatively extreme and polarized influence on coastal litter accumulation in the south-eastern model compared to the south-western model. One plausible explanation for the difference in impact timing is the presence of islands in each region. The south-eastern region of South Korea exhibits a relatively higher concentration of islands, and these islands, on average, are larger compared to the designated south-western region. These islands may act as obstacles for litter originating from fishing activities, impeding its movement towards the coastal region in the south-eastern area.

Aquaculture exhibits the least impact compared to other factors in the south-western region, while it has the greatest impact in the south-eastern region. The intensity of aquaculture activities was found to be higher in the south-western region compared to the south-eastern region. From 2018 to 2021, the average catch per site was 2287.54 kg in the south-western region, while it was 383.21 kg in the south-eastern region. The substantial disparity in the relative contributions of fishing activities between different regions may suggest the presence of additional independent variables influencing the accumulation of ocean-sourced coastal waste. The inclusion of additional independent variables could reconcile distinct regression models based on regions, potentially enhancing explanatory power.

Furthermore, the interpretation of relative importance merits attention in translation. It is important to note that the relative importance of an independent variable within the developed regression model cannot be easily translated into the actual impact on waste accumulation. This limitation primarily stems from data insufficiency. If data encompass both accuracy and quantity, more advanced techniques can be harnessed to formulate highly precise statistical models, particularly those employed in big data analysis. Nevertheless, we contend that the model we propose has the potential to provide valuable managerial insights to personnel directly responsible for coastal waste management. These insights can assist in establishing managerial priorities within fishery activities aimed at reducing waste generation.

5. Conclusions

This study has formulated time series models to investigate the correlation between fishing activities and coastal waste accumulation in distinct regions. A comparative analysis with conventional models, neglecting temporal variations, reveals substantial discrepancies in their explanatory capacities. In the south-western sea area, the time series model notably surpasses the conventional model, achieving an R-square value of 0.544 compared to 0.168. Similarly, in the south-eastern sea area, the time series model exhibits a significant enhancement in explanatory power, yielding an R-square value of 0.5105 in contrast to 0.078 for the conventional model. These outcomes underscore the importance of accounting for temporal dynamics to comprehend the temporal variations in the onset and accumulation of coastal waste, thereby enriching our understanding of the intricate relationship between fishing activities and coastal litter. The applied models also disclose a temporal delay before the impact of fishing activities manifests as actual litter accumulation on the coast. The regional model for fisheries-induced marine litter presented in this study is anticipated to serve as a foundation for developing a more comprehensive model that incorporates socioeconomic factors in the future.

However, it is imperative to acknowledge the need for further research to explore potential additional independent variables influencing ocean-sourced coastal waste accumulation. Furthermore, the pursuit of more sophisticated model generation, leveraging recent advancements in artificial intelligence technology, could contribute to the development of more robust and reasonable statistical models.

Author Contributions: S.-H.L.: conceptualization, data curation, writing—original draft preparation, supervision. S.-K.H.: writing—review and editing. J.L.: methodology, formal analysis, software, writing—review and editing. J.-W.Y.: data curation. H.-T.K.: writing—reviewing. T.-H.J.: data curation and editing. All authors have read and agreed to the published version of the manuscript.

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