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Correlation between fishing yield and microplastic levels across nations

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Abstract. This research looks into the association between fishing and microplastic contamination across countries, with a particular focus on how the growth of microplastic levels can impact fishery production. Through the use of a mixed-effect model we were able to look through data from 100 nations during the period 1990-2021, where fishery yield data was extracted from The World Bank and microplastic concentration data was obtained from the National Centers for Environmental Information; population data served as a control variable in our analysis. We found that there is indeed a significant negative correlation between levels of microplastics and fishing yield: an increase by 1 piece of microplastic per cubic meter leads to decrease in fishing yield by anything between 65 and 100 metric tonnes (95% confidence interval). This relationship held true for about 93% of all coastal countries studied. To accommodate for differences amongst nations, we introduced random intercepts and slopes in our mixed-effect model which helped capture variations specific to each country while still identifying an overarching pattern. The research we are doing is on the connection between fish catches and microplastic pollution which takes place in the different countries of the world, where we focus more on how high microplastic levels influence fishery production. Having made use of a mixed-effect model, we have been able to look at data that represents 100 nations within the period of time between 1990 and 2021; The World Bank provided us with fishery yield data while microplastic concentration data came from the National Centers for Environmental Information. In addition to these variables, population data was used as a control variable. The summary of our analysis points towards a significant inverse relationship noted between microplastic levels and fishing yield: an increase by one piece of plastic results in a decline by somewhere between 65 to 100 metric tonnes (95% confidence interval). This generalization held true for about 93% coastal countries considered under this study. To capture specific variations among nations but also identify an overall trend line while dealing with inter-country variability, random intercepts and slope components were included as part of our mixed-effect model methodology.

Keywords: Microplastic levels, Fishing yield, Mixed Effect Model, Correlation.

1. Introduction

This investigation is intended to address an area of incomplete data coverage that exists in contemporary research and to offer a quantitative scrutiny of the levels at which microplastics impinge on fish catch. The outcome will provide some clues about the true nature of the effect produced by growing microplastic concentrations on reducing fishing yields, and hence such information can be highly

informative regarding two aspects: the gravity of microplastic pollution itself— particularly in its implication through the fish industry — and also onto public health.
The purpose of the investigation is to explore the relationship of fish catch and contamination of microplastics for different countries with special attention paid to the issue that the increase in microplastic levels in oceans may have an impact on production from fishery. We assume a negative correlation between microplastic levels and fishing yield.

Our study will consist of two stages:

1) Determining a general relationship between the level of microplastics and fish catch globally.

2) Analysis of 100 selected countries in more detail to identify specific trends.

The research aims to bridge a void in the present literature. This will be achieved by quantitatively analyzing the relationship between levels of microplastics and fishing yields. Consequently, it is hoped that this information will help shed light on how high the impact can rise due to the increase in levels of microplastic, further affecting fish yields which in turn would mean — directly or indirectly — serious implications towards microplastic pollution as well as possible repercussions on public health through fisheries.

The research intends to bridge an identified gap in existing studies by quantitatively analyzing the influence of microplastic levels on fishing yields. The findings will provide a better understanding of the impact that elevated microplastic levels have contributed towards lowering fish catches thus in turn, offering important cues regarding the severity of microplastic pollution — and through fish, effects on public health — as a major source of food.

2. Literature Review

2.1. Microplastics: Sources and Environmental Impact

Microplastics are tiny plastic particles measuring less than 5 mm, and they have emerged as a considerable environmental worry in the last few years. Some researchers pinpointed synthetic textiles, city dust, and tire wear as the major origins of microplastics — which are steadily becoming larger in quantity and contribution to their production plus dramatic increment since 1950s [1, 2].

Cole *et al.* analyzed the origins, dispersion, and effects on living organisms in sea waters from minute pieces of plastic and came up with an overview that covered all important aspects [3]. They brought to attention that microplastics have a capability of absorbing polychlorinated biphenyls which are organic micropollutants from surrounding waters and laterally passing these materials into fauna; thus, this transition creates threats for marine systems and indirectly for human health when people consume seafood as part of their diet.

Additional investigations conducted by the team of Rochman revealed that fish which came into contact with microplastics also manifested alterations at the genetic level alongside indications of hepatic stress [4]. These observed phenotypic changes implicate potential implications to marine life at large, hence underscoring those critical elements encapsulated in an appreciation of the dynamics of microplastic pollution vis-a-vis the oceans — a keen recognition from fisheries and related ecosystems.

2.2. Impact of Overfishing on Fishing Yields

Global fishing yields' reduction is already the object of many investigations. Pauly and Zeller in 2016 made a comprehensive analysis by reconstructing global marine fishery catch data from 1950 to 2010 [5]. It was found that the declines are steeper than what official data had reported, also that the global catches were more than those reported.

Perissi *et al.* advanced this research by offering time-varying patterns of fishery overexploitation, finding that the decrease in fish yield is as a result of high depletion of fish stocks [6]. They come up with a model where overfishing leads to collapse in fish population hence negative yield.

In addition to these investigations, Costello *et al.* examined the situation of 4,713 fisheries across the world — which accounts for 78% of global reported fish catch [7]. They discovered that although 32%

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of those fisheries were in bad biological shape, good managerial adjustments could result in large increases of abundance, harvest and profit for most fisheries.

2.3. Mathematical Modeling of Microplastics in Marine Environments

Microplastics behavior and distribution in marine environments have been tackled by quite a number of modeling studies. In 2020, Chaturvedi *et al.* used mathematical modeling to study the influence of microplastics on ocean surfaces [8]. Their model unveiled details on the propagation and buildup of microplastics in various oceanic zones.

Expanding from this work, Koelmans *et al.* created a model that can be used to assess the movement and future location of nano- as well as microplastics in water bodies [9]. In their research, they brought attention to the significance of different physical and chemical processes in studying how microplastics are distributed in marine systems.

2.4. Public Perception and Awareness of Microplastics

The key to the success of any measures or regulations is understanding how microplastics are seen by the public. In their study, Henderson and Green carried out a detailed overview of the perception that people have on microplastics [10]. They discovered that although awareness among the public is rising steadily about microplastics, there remains large discrepancies in knowledge about where they come from and what their impacts are.

Anderson and his colleagues, in 2016, conducted additional research on the matter through a study based on the public views held in Europe [11]. The outcomes of their study pointed out that while the general public tended to consider microplastics as a serious environmental threat there was lack of awareness about individual roles contributing to the issue.

2.5. Mixed Effect Models in Environmental Studies

In environmental work mixed effect models are widely used because they can manage data structures that are difficult to unravel and illustrated how these models permit investigations into data possessing innate correlation — a most effective resource in cases where multiple locations or points in time are involved [12].

Zuur *et al.* developed a deeper understanding and introduced further ideas on the use of mixed effect models in ecology, which help to take into account the hierarchical nature of many environmental datasets [13]. Their contribution has significantly advanced the use of such methodologies and now they are widely employed in different types of ecological investigations.

2.6. Restricted Maximum Likelihood Estimation in Statistical Modeling

Restricted Maximum Likelihood Estimation (ReML) is an important approach when fitting mixed effects models [14]. Henson and Friston pointed out that it allows one to make efficient joint estimation of model parameters along with hyperparameters, under sensible partitioning of effective degrees of freedom [15].

Patterson and Thompson brought ReML to the world in a ground-breaking paper, which allows us to get estimates of variance components unbiasedly in linear mixed models [16]. Since that time, ReML has turned into the most common method for estimating parameters in models with mixed effects because it offers lower bias than other methods like maximum likelihood estimation.

2.7. Research Gap and Contribution of the Current Study

Although the previously mentioned studies have greatly helped us in understanding microplastics plus fishing yields and statistical modeling, there is a wide gap of research that directly links changes in fishing yields (on a global level) to microplastic levels. Our work intends to fill this gap by offering quantitative assessment on the association between these two factors from many nations, using sophisticated statistical approaches like mixed effect models and ReML estimation.

The use of such broad-based interdisciplinary model — that is established by assimilating information from various fields such as marine biology, environmental science, fisheries management and statistical modeling — will enable our study to have a complete portrayal of the effects of microplastic pollution on global fish catch biomass. The approach through more than one field will inject good sense in both environmental science and fisheries management which can be used in policymaking and conservation activities down the line.

3. Methods

3.1. Data Collection and Processing

We collected data from three primary sources, focusing on the period from 1990 to 2021. This timeframe was chosen because it represents the most recent period with comprehensive and accurate data availability, particularly for microplastic levels.

3.1.1. Fishing Yield Data. We obtained fishing yield data from THE WORLD BANK database [17]. This dataset measures the total fisheries production, including the volume of aquatic species caught by a country for commercial, industrial, recreational, and subsistence purposes. The data is reported in metric tons and includes fish captured inland. While it excludes aquaculture production and some freshwater catches, it serves as a good indicator of marine fish catch.

3.1.2. Microplastic Level Data. Microplastic level data was sourced from the National Centers for Environmental Information [18]. The data represents the concentration of microplastic particles per cubic meter of seawater in each country's Exclusive Economic Zone (EEZ).

3.1.3. Population Data. Population data for each country was also obtained from THE WORLD BANK database to account for demographic factors that might influence fishing yield [19].

3.1.4. Data Processing. We processed the raw data to align the time series and geographical information across all datasets. We used the Marine Regions database and Google Maps API to match the microplastic measurement locations with the corresponding countries' EEZs.

3.2. Statistical Analysis

3.2.1. Mixed Effect Model. We employed a mixed effect model to analyze the relationship between fishing yield and microplastic levels while accounting for country-specific variations. This model was chosen for its ability to handle hierarchical data structures and capture both fixed and random effects. The general form of our mixed effect model is:

$$Y_{i,j} = \left(\beta_0 \pm u_{0,j}\right) + \left(\beta_1 \pm u_{1,j}\right)M_{i,j} + \beta_2 P_{i,j} + \beta_3 T_{i,j} + \epsilon_{i,j} \tag{1}$$

Where:

- $Y_{i,j}$ is the fishing yield for the i^{th} observation in country j.
- $M_{i,j}$ is the microplastic level for the i^{th} observation in the country j.
- $P_{i,j}$ is the population for the i^{th} observation in the country j.
- $T_{i,j}$ is the time variable (year).
- β_0 is the fixed intercept.
- β_1, β_2, and β_3 are the fixed effect coefficients.
- $u_{1,j}$ is the random intercept for country j.
- $\epsilon_{i,j}$ is the error term.

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3.2.2. Model Fitting. We used the statsmodels.formula.api package in Python to fit the mixed effect model. The model was fitted using Restricted Maximum Likelihood Estimation (ReML) to obtain unbiased estimates of the variance components.

3.2.3. Variable Selection. We considered several factors in our model:

1) Microplastic levels: Our primary variable of interest.
2) Population: To account for demographic influences on fishing yield.
3) Time: To capture any temporal trends not explained by other variables.

We conducted sensitivity analyses to determine the optimal combination of variables that best explained the variation in fishing yield while avoiding overfitting.

3.2.4. Model Validation. We validated our model using the following methods:

1) Residual analysis: To check for normality and homoscedasticity of residuals.
2) Cook's distance: To identify influential data points.
3) Variance Inflation Factor (VIF): To check for multicollinearity among predictors.

3.3. Correlation Analysis

We performed correlation analyses to examine the relationship between fishing yield and microplastic levels at both global and national levels.

3.3.1. Global Analysis. We calculated the overall correlation coefficient between fishing yield and microplastic levels across all countries and years.

3.3.2. Country-Specific Analysis. For each of the 100 countries in our study, we calculated individual correlation coefficients to identify country-specific trends.

3.4. Visualization

We created several visualizations to aid in the interpretation of our results:

- Scatter plots: To visualize the relationship between fishing yield and microplastic levels.
- Heat maps: To display the strength and direction of correlations across different countries.
- Time series plots: To show trends in fishing yield and microplastic levels over time.

3.5. Software and Tools

All statistical analyses were performed using Python 3.8. We used the following key libraries:

- pandas for data manipulation
- statsmodels for statistical modeling
- scipy for statistical tests
- matplotlib and seaborn for data visualization

4. Results

4.1. Overall Relationship

Starting off from a broader standpoint in our analysis, we looked into the global overview between fishing yields and microplastic levels. The first results unveiled an inconspicuous albeit uniform negative association worldwide on a global level (refer to Figure 1 and Figure 2). This broad stroke pattern laid the groundwork for delving deeper into understanding how this relationship plays out in different nations and zones.

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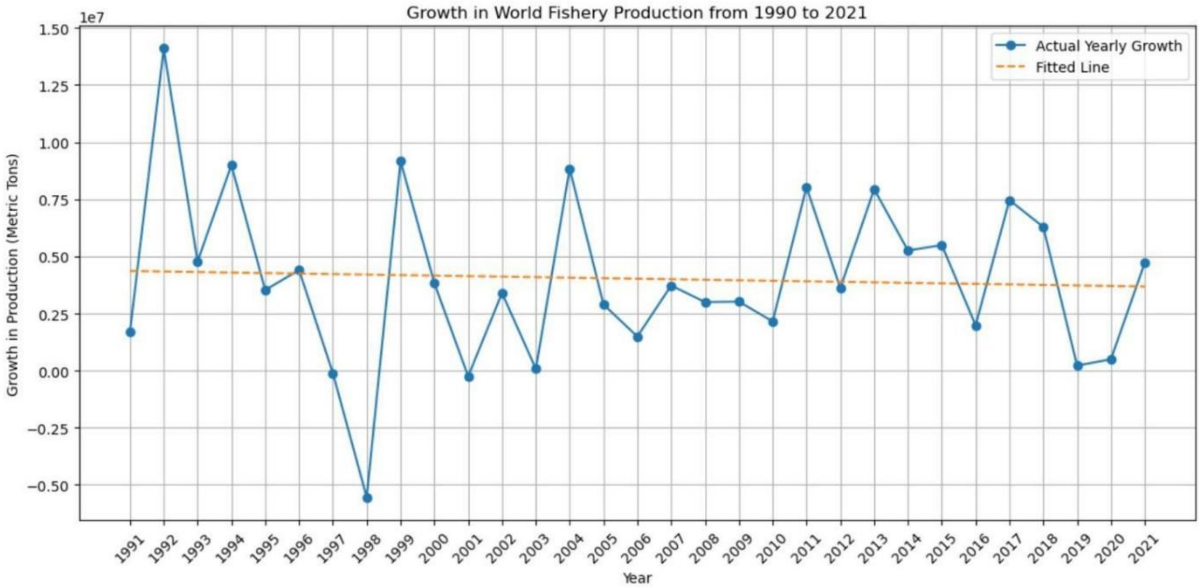

Figure 1. Overall Pattern for Fishing Yield.

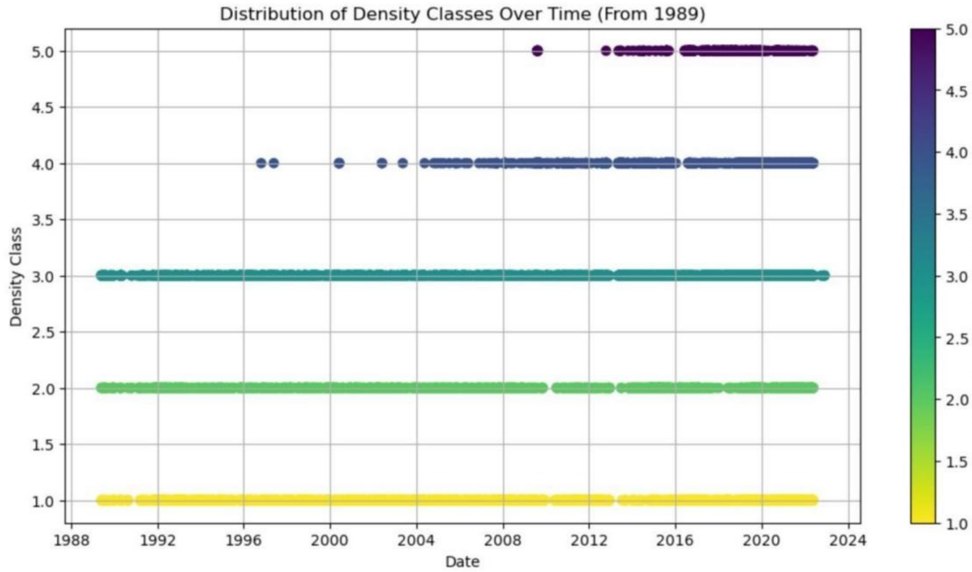

Figure 2. Overall Pattern for Microplastics Levels.

Figure 1 shows a trend of decrease in fish catch where every next but smaller peak. This pictorial description clearly reveals that each peak is smaller than the one before it, and there are no exceptions as all points to the downward direction without any doubt. In Figure 2 we identified numerical density levels for microplastic aggregations by very subjective representation scale; from 'Very Low' (1) to 'Very High' (5). The revealed picture demonstrates an abrupt rise during observed years between 1990 and 2022.

An investigation into these worldwide phenomena — the decreasing curve of fish catch against the growing mound of microplastics — leads us to an inference of reciprocal nature between these two variables. This initial observation lays foundation for our assumption of anti-correlation as the level of microplastics rise and fishing yield plunge, which we have then probed through extensive statistical scrutiny.

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4.2. Data for the Function

We restricted our analysis to nations that have comprehensive data availability in all three datasets—the median, 25th percentile and 75th percentile of microplastic levels. One hundred countries satisfied this condition, comprising our study sample.

The Figure 3 illustrates a geographic representation of the nations produced through 'geopandas,' a Python library. On this map, countries shown in dark blue are part of our study. Our sample is quite rich as it covers most coastal countries, which would have otherwise been missed out — this limitation notwithstanding, since some countries were not included in the geopandas database. The wide coverage will facilitate an elaborate global level analysis on the connection between microplastic levels and fish production hence even with that limitation we can still say it was good work done.

Figure 4 displays the spatiotemporal disparities of data availability within our sample. The dark blue bars represent the years where a specific country has comprehensive data in all three datasets (median, 25th percentile, and 75th percentile of microplastic levels). Through this visual summary, we aim to reveal the temporal continuity of information used in our analysis and to point out any time lapses that might be present due to lack of uniform data collection efforts across the countries under consideration.

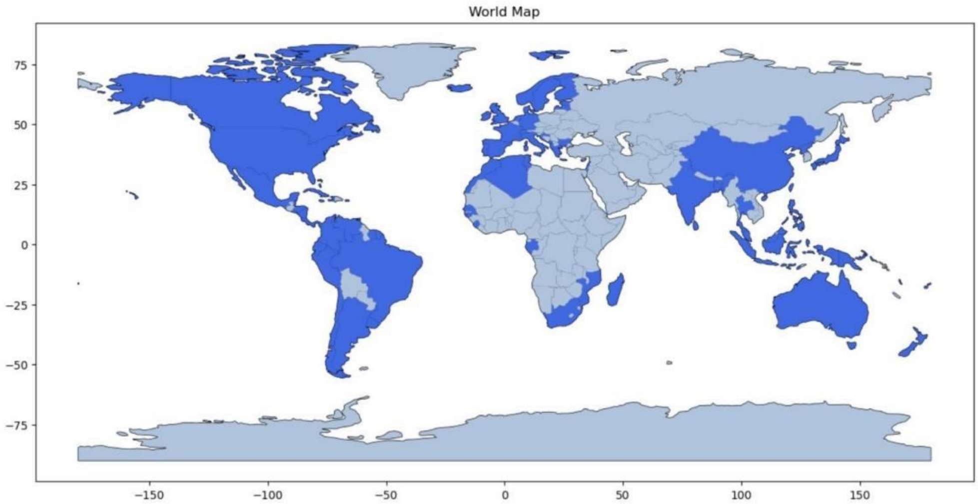

Figure 3. The Distribution of Countries.

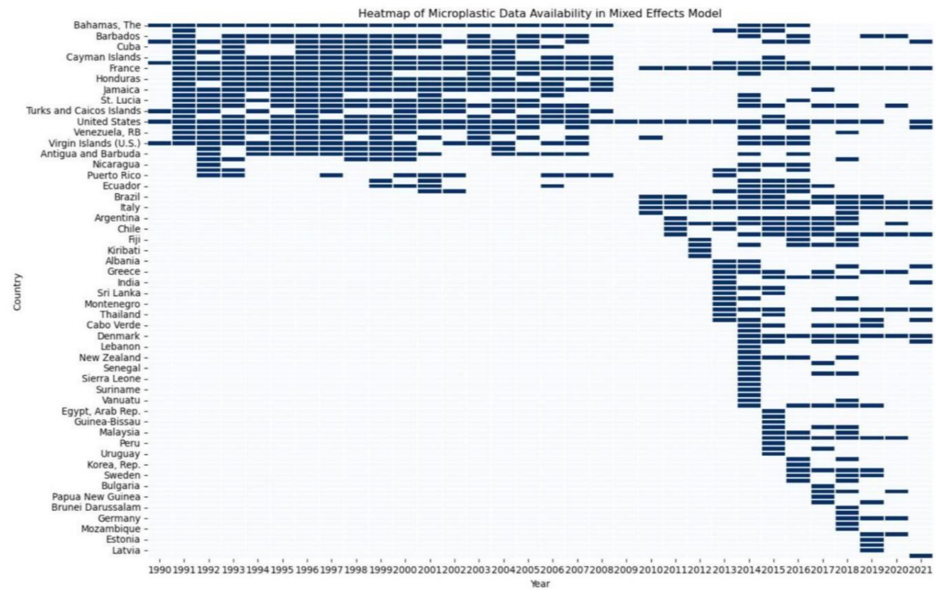

Figure 4. Heatmap of microplastic data availability in mixed effects model.

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4.3. Mixed Effect Model with Random Intercept

Table 1. Summary of situation 1-12 of the coefficient and p-value.

		Coefficient	p-value
Median Group	Situation 1	-45.623	0.068
	Situation 2	-64.198	0.052
	Situation 3	-46.576	0.065
	Situation 4	-65.473	0.048
25th percentile Group	Situation 5	-73.980	0.033
	Situation 6	-100.585	0.028
	Situation 7	-75.371	0.031
	Situation 8	-102.446	0.026
75th percentile Group	Situation 9	-8.157	0.337
	Situation 10	-14.432	0.198
	Situation 11	-8.411	0.327
	Situation 12	-14.791	0.189

Mixed effect model application endorsed the initial assumption leading to a discovery of negative relationship between fishing yield and microplastic levels. In this paper we tabled comprehensive results summary for all twelve scenarios we looked into, as shown in Table 1. The primary highlights of our analysis were two statistical measures which are very significant in such analysis— the coefficients which show the direction and strength of relationships, and p-values that give us an idea on statistical significance level. These findings provide strong support for robust evidence underlining inverse correlation that exists between microplastic contamination and fish harvest across varying modeling situations.

The results of our analysis displayed different degrees of statistical significance among the percentile groupings and model application circumstances. The coefficients of all variables in groups "median" and "25th percentile" were significant at a 10% confidence level. Remarkably, microplastics' coefficients within the "25th percentile" group attained a 5% level of significance. It was noted that introduction of a delayed effect related to microplastics in the models consistently led to better statistical significance.

The "75th percentile" group did not show any significant results even though it was in the direction we expected, likely due to inconsistency of the 75th percentile data over years within countries— perhaps because of small sample size. As a result, we dropped the "75th percentile" group from further analysis, including those that involved random slope models. On the other hand, stability seen in the "25th percentile" group may be attributed to countervailing forces.

The "median" group results clustered around a coefficient of -65, and the "25th percentile" group centered approximately -80. These coefficients showed notable consistency under different model conditions, suggesting the strength of our conclusions.

To sum up our findings about the overall relationship between fish catch and microplastic levels in oceans, the most robust range of estimates indicates that for every additional piece of plastic per cubic meter found in ocean waters, the amount of fish a country catches decreases by between 65 to 100 metric tons.

5. Discussion

5.1. Comparison with Previous Studies and Evaluation of Our Model

This research fills parts of the information gap of the factors that would affect the fishing yield. It gives a general conclusion about how the increase of microplastics in the ocean might affect fisheries. Compared with one of the most related papers written by Perissi *et al.*, who have researched how overexploitation in fisheries leads to the reduction in fishery production [6]. This paper has not used a rigorous system to do the causal inference to ensure that the fishing yield will reduce when the microplastic pollution levels in the ocean are worse off, but it indeed provides insight to it.

The use of a mixed-effect model has both advantages and disadvantages in our research. The benefits of the mixed-effect model are mainly shown by its capacity to deal with correlation between complex data. The existence of random effects, both random slope and random intercept, ensures that the variability across nations will not affect us in finding the general relationship we want. However, as our data is not complete, the process of analysis by the mixed effect model will be affected, thus reducing the accuracy of the result. Besides, we have not considered the factor of ocean currents. The actual situation is that the ocean current will bring microplastics from one country to another. The measurement of microplastic is not exact as we are not sure that all microplastic has been collected. The hand-picking methods and other methods that are not considered will also decrease the accuracy of our result.

The optimal situation is that the dataset collects all the microplastics in that area for every measurement, and it is better to match the location of measurement with the fishing yield in that location. The incompleteness of the "median" group, "75th percentile" group, and "25th percentile" group can also be eliminated in this situation.

The uses of the model without and with the random slope do not conflict with each other. As we do the research from two different perspectives, the insignificance of the coefficient of the microplastic levels does not provide evidence of the unreliability of the first result. It is worth noticing that both the coefficient of "Year" and "Population" confirm the stability of our model. The trend of the slopes shown in the situation of considering the random slopes also supports our conclusion.

5.2. Significance

In this global research, we provide insight into how the pollution created by humans eventually leads to a negative influence on themselves according to the biochemical cycle. The microplastic absorbed by fish will be captured by humans. When they are provided in the market, they will become goods and services that will be consumed by people. The microplastic will eventually get into people's bodies and cause issues in public health. Without attention to the increased amount of microplastics, humans might suffer from the pain created by ourselves.

Moreover, the persistent nature of microplastics means that they do not break down easily. This will result in long-term environmental accumulation. The continuous growth in plastic production and inadequate disposal and recycling mechanisms require people to raise awareness of this issue.

In this paper, the 36 valid results all show that there is a universal trend for the negative correlation between microplastic levels and fishing yield. As microplastic pollution continues to be a global concern, its implications for fisheries and the broader environment necessitate urgent and comprehensive attention. Therefore, such research can provide valuable insights into the health of aquatic ecosystems and help ensure the long-term sustainability of fisheries.

5.3. Suggestions

As citizens, we should raise awareness of the seriousness of pollution and realize the significance of protecting our environment. There is an estimation that half of ocean plastic pollution comes from some 4.5 million fishing vessels [20]. For fisheries, it is vital to provide an environmentally friendly way of fishing. Fisheries are one of the most important providers of plastic pollution. The use of fishing nets and boats should be improved.

6. Conclusion

The study adds to the increasing evidence base of harm done by microplastics to marine systems and numerically quantifies an investigation that can be conducted in the future on the modes through which fish population impacts occur as a result of microplastic effects. Hence, going ahead with efforts that integrate ocean management and pollution control would be a wise decision and there should be more investigations into causality — while also coming up with ways to mitigate it effectively. We have reached the same conclusion as others. The evidence is constantly increasing that microplastics are harmful to marine systems. We have also developed a quantitative basis, which will be useful for future research aimed at identifying the mechanisms of influence of microplastics on fish population. Henceforth, the coordination of efforts between ocean governance and pollution control will be essential, pending yet more research on causative relationships with a view to designing mitigation strategies that are effective.

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