From Ocean Changes to Conflict: Fishery-Related Militarized Disputes in a Warming World *(Preliminary Title)*

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Abstract

As climate change reshapes the world's oceans, the battle for dwindling fish stocks intensifies, leading to an alarming rise in fishery-related militarized disputes (MIDs). Fishery-related militarized disputes (MIDs) represent a significant and growing area of geopolitical tension, exacerbated by shifting fish distributions due to climate change. This project analyzes data on fishery-related MIDs. By integrating historical patterns with climate change projections, we identify how alterations in climatological factors and fish distributions influence the frequency of MIDs. Our findings highlight regions and conditions most susceptible to future disputes, providing valuable insights for policymakers and international bodies to preempt and mitigate conflict. This research underscores the necessity for adaptive fisheries management and international cooperation to address the dual challenges of environmental change and geopolitical stability.

Keywords: Fisheries Management, Conflict Mitigation, Marine Resources

1 Main

While it is well-established that climate change is affecting marine ecosystems and fish distributions [1–3], the specific impact of these changes on the frequency and nature of fishery-related militarized disputes (MIDs) remains underexplored. Existing literature has highlighted the broader environmental and geopolitical effects of climate change [4–7]. Furthermore, in 2018, the United Nations' Food and Agriculture Organization (FAO) released an extensive report detailing the impacts of climate change on fisheries and aquaculture [8].

Other research has examined fishery-related conflicts, such as the study by Spijkers et al. (2019), which reveals an alarming increase in global fisheries conflicts over the past two decades [9]. Furthermore, there is emerging evidence highlighting regional tensions, particularly in the South China Sea [10], where studies indicate significant disputes affecting bilateral relations, notably between China and South Korea [11]. Recent work also suggests that climate change may exacerbate these conflicts, underscoring the urgency of understanding its implications for marine resource governance [12].

We take up the challenge posed by previous research by providing robust statistical evidence at scale regarding the relationship between shifts in fish stocks due to climate change and the resulting conflicts over fishery resources. Our research seeks to address this gap by identifying the precise mechanisms through which environmental changes impact the likelihood of fishery-related disputes, particularly through alterations in fish stock and the value derived from these resources. Ultimately, we seek to provide valuable insights that can inform strategies for anticipating and mitigating future conflicts.

Employing logistic regression across 31,484 unique country-directed dyads from 1985 to 2014, we investigate how changes in fish value and stock—sourced from the FAO—of both the challenger and target states influence the probability of fishery-related militarized disputes (MIDs). This analysis incorporates a range of socio-political and environmental control variables, aiming to provide insight into the complex relationships between climate shifts and geopolitical tensions within the context of fisheries management. Notably, our findings suggest that when the challenger's change in fish resources is low while the target's is high, the probability of fishery-related MIDs significantly increases.

2 Results

To contextualize and preface our findings, we begin with a series of visual representations that illustrate the dynamics of fishery-related disputes and fish value levels across several time periods. Figures 1-3 below provide a snapshot of fishery-related disputes and fish levels in 2014, 2004, and 1994, respectively. These maps illustrate the distribution of the monetary value of fish catches across countries engaged in conflicts. The highlighted countries indicate those that participated in fishery-related militarized disputes (MIDs), with red lines denoting the pairs of countries involved in these disputes. This visual representation effectively demonstrates how variations in fish counts correlate with ongoing disputes, offering valuable insights into the relationships between fishery resources and conflict dynamics over time.

Figure 1 for 2014 highlights a particularly volatile period in the South China Sea, where China, South Korea, the Philippines, and Vietnam exhibited varying changes in fish value compared to the previous year while simultaneously engaging in fishery-related militarized disputes (MIDs). This situation underscores the complex interplay between fluctuating fishery resources and escalating geopolitical tensions in the region.

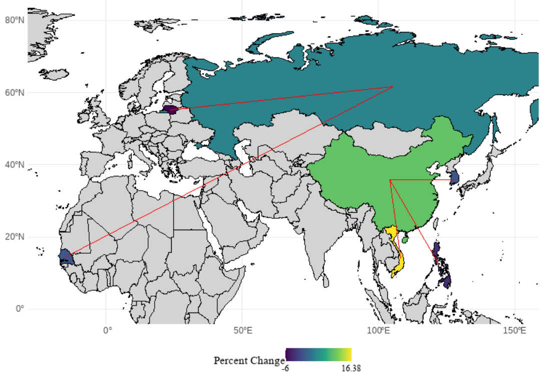

Fig. 1 Percent Change of Fishing Values in Countries with Fishery-related MIDs (2014)

Note: Values reported come from the FAO FishStat Database. Disputes occur between Russia and Lithuania, Senegal and Russia, China and Vietnam, China and the Philippines, and the Republic of Korea and China.

In 2004, we observe notable fishery conflicts across the Middle East and Southeast Asia, reflecting heightened tensions in these regions over marine resources (see Figure 2). Countries such as Iran and Qatar, Iran and the United Arab Emirates, India and Pakistan, Myanmar and Thailand, and Thailand and Indonesia were involved in disputes related to fishing rights and access to valuable fish stocks. Southeast Asian states, in particular, experienced significant increases in fish catch value from 2003, while the Middle Eastern countries faced declines. This disparity evidences changing patterns in fishery resources, likely related to international climate events such as El Niño-Southern Oscillation (ENSO), which can profoundly impact marine ecosystems and exacerbate competition for dwindling resources.

In 1994, we observe a stark contrast in fishery-related income changes between Greece and Turkey, with Turkey experiencing a significant increase while Greece's income remains particularly low (see Figure 3). Additionally, Vietnam recorded a notably strong year in terms of revenue generated from fish catches. This situation is further complicated by ongoing conflicts between Vietnam and its neighbors, China and the Philippines, both of which reported lower levels of fishery income. These dynamics highlight the intricate relationships between regional fisheries and the potential for disputes over marine resources during this period.

The historical occurrences highlighted in the figures 1-2 of fishery-related disputes across different regions and time periods suggest a relationship between fluctuations in fishery resources and geopolitical tensions. However, our next step is to rigorously investigate whether this anecdotal evidence holds statistically. By employing robust quantitative methods, we aim to substantiate these observations and provide a comprehensive understanding of the factors driving fishery-related conflicts.

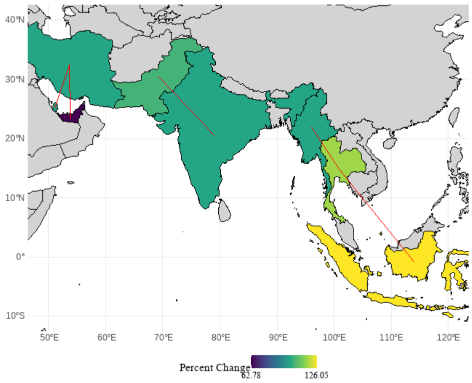

Fig. 2 Percent Change of Fishing Values in Countries with Fishery-related MIDs (2004)

Note: Values reported come from the FAO FishStat Database. Disputes occur between the following countries: Iran and Qatar, Iran and the United Arab Emirates, India and Pakistan, Myanmar and Thailand, and Thailand and Indonesia.

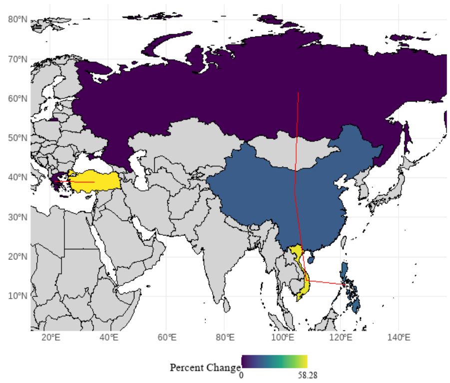

Fig. 3 Percent Change of Fishing Values in Countries with Fishery-related MIDs (1994)

Note: Values reported come from the FAO FishStat Database. Disputes occur between the following countries: Greece and Turkey, Russia and China, China and Vietnam, and Vietnam and the Philippines. Please note that the dispute between Nicaragua and Colombia is not shown.

2.1 Clarifying the Connections: Fisheries Resources and Dispute Probability

This analysis employs logistic regression models to examine the factors influencing the occurrence of fishery-related militarized disputes (MIDs). Two separate models are used: one to assess the impact of the percent change in the value of fish and another to evaluate the effect of the percent change in the count of fish. Both models have the same binary outcome variable, fishery-related MID, which indicates the presence or absence of a fishery-related dispute in a given year. The unit of analysis in these models is dyad-year, reflecting the interactions between pairs of countries and their annual fishing characteristics. This approach allows for a nuanced examination of how changes in fish value and fish count relate to the likelihood of disputes. The output of this analysis is shown in Table 1. Detailed information on data sources and variable transformations can be found in the Methods section.

Table 1 Logistic Regression Results: Fishing Value and Fishing Number

	Dependent variable: fishy_mid	
	(1)	(2)
Challenger Change in Fish Value	-0.066***	
	(0.027)	
Target Change in Fish Value	0.006**	
	(0.002)	
Challenger Change in Fish Number		-0.239***
		(0.058)
Target Change in Fish Number		0.011*
		(0.005)
ONI ENSO	22.073***	22.122***
	(1.669)	(1.669)
China Sea	−0.662	−0.640
	(0.410)	(0.410)
ONI ENSO X China Sea	1.721***	1.714***
	(0.453)	(0.453)
Challenger Total Capabilities	15.611***	15.543***
	(2.725)	(2.724)
Challenger Regime Type	−0.004	−0.004
	(0.025)	(0.025)
Target Regime Type	0.054*	0.052*
	(0.023)	(0.023)
Capital Distance	−0.0002	−0.0002*
	(0.0001)	(0.0001)
Challenger Teleconnections	−3.013**	−3.127**
	(1.033)	(1.032)
Target Teleconnections	3.542***	3.578***
	(0.763)	(0.763)
Constant	−9.364***	−9.310***
	(0.913)	(0.913)
Observations	20,410	20,410
Log Likelihood	−316.092	−316.597
Akaike Inf. Crit.	720.183	721.195

Significance Levels: *p¡0.05; **p¡0.01; ***p¡0.001.
Note: Standard errors are clustered by dyad. Factor variable Contiguity is not shown in this output. Challenger coefficients for fish number and value have been scaled by 1×10^{19}, and target coefficients for fish number and value have been scaled by 1×10^{9} for clearer interpretation.

Based on the findings presented in Table 1, our results provide substantial evidence on how various factors contribute to fishery disputes. For instance, also supported by previous literature [13], we find that the interaction of El Niño-Southern Oscillation (ENSO) events and dynamics in the South China Sea significantly increases the probability of militarized fishery disputes. Furthermore, our analysis reveals that the military capabilities of the challenger state play a crucial role; higher military capabilities correlate with an increased likelihood of disputes. Additionally, countries' teleconnections, which capture their exposure to climate variability, further elevate the likelihood of fishery-related conflicts. Notably, our research specifically focuses on the dynamics of fish-related resource counts and values. As illustrated in the coefficient plots below, there is a clear relationship between fishing metrics and the likelihood of conflict. Specifically, a negative change in the challenger's fishing metrics coupled with a positive change in the target's fishing counts is associated with a heightened probability of fishery disputes. This trend is consistent across both the quantity of fish and the monetary value derived from fishing activities.

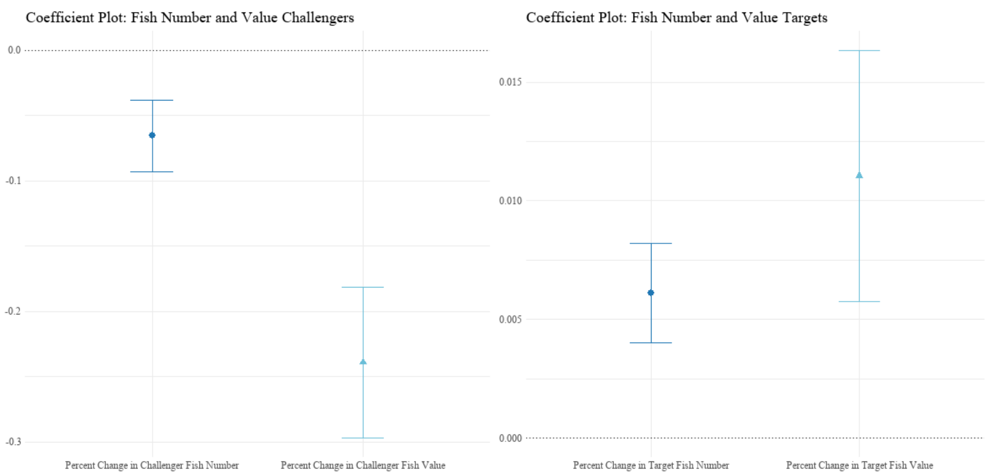

Fig. 4 Coefficient Plots for Fish Count and Value

Note: These coefficients are derived from the estimations in Table 1, focusing on our main independent variables of interest. We observe that when the Target's percent change in fishing value and number caught *increase* from the previous year and the Challenger's percent change *decrease*, there is an increased likelihood of fishery MIDs occurring. Source: FAO FishStat Database.

Capturing the logit probability of the percent change from previous years across this data yields a less intuitive interpretation. Therefore, we present substantive results in terms of medians and standard deviations. When analyzing the likelihood of fishery-related militarized disputes (MIDs), the baseline probability of such an event occurring is extremely low, at approximately 0.00003% when both the Challenger Fish Value and the Target Fish Value are at their median levels. In contrast, this probability increases dramatically to 23.81% when the Target Fish Value is increased by one standard deviation above its median while the Challenger Fish Value is decreased by one standard deviation below its median. Additionally, the baseline probability for fish numbers is also minimal, at about 0.00003%. However, a similar scenario where the Target Fish Number is increased by one standard deviation above its median and the Challenger Fish Number is decreased by one standard deviation below its median results in a probability of 12.13%. These substantial increases in probability for both fish values and fish numbers underscore that significant deviations from median levels can greatly enhance the likelihood of a fishy MID event, indicating the critical role that changes in fishery values and counts play in the escalation of fishery-related conflicts.

3 Discussion

[This section is sparse. I have included the Random Forest Variable Importance analysis to provide a more substantive discussion on which variables are particularly meaningful in predicting Fishy MIDs (e.g. as capabilities and target fish resources). We should discuss what else to add to this section.]

3.1 Random Forest Variable Importance

We utilize the Random Forest to assess the importance of various variables in predicting fishery-related MIDs. Specifically, we focus on the Mean Decrease in Gini score, a metric that quantifies the contribution of each variable to the model's predictive performance. This approach helps us identify which predictors have the most substantial impact on the outcome of interest. Our findings reveal that among the variables assessed, the total military capabilities of the challenger, along with changes in challenger fish value and count from the previous year, are particularly significant. These variables exhibit a high Mean Decrease in Gini, indicating their strong influence on the likelihood of fishery-related disputes. This insight underscores the critical role of military power and changes in fishing metrics in understanding the dynamics of international conflicts over fisheries.

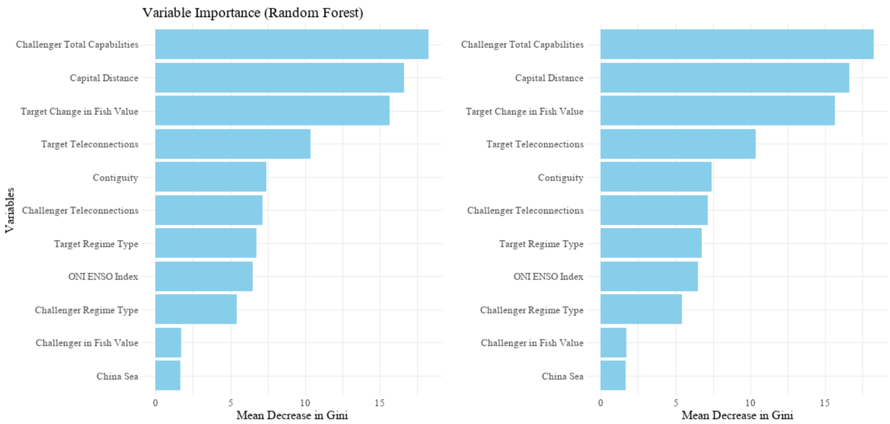

Fig. 5 Random Forest Variable Importance: Gini values across IVs

Note: This figure displays the Gini values of the random forest variable importance, including all the variables of interest. These values provide insight not only into the relative importance of each variable in predicting fishery MIDs and the model's accuracy but also into which variables are most substantively predictive.

3.2 Implications of Shifting Fish Stocks for Maritime Conflict

[This should act as the "conclusion" and still needs to be written]

4 Methods

This section details the data, methods, and sensitivity checks employed in this analysis. It begins with an overview of the data sources and the variables utilized in the study. Next, the discussion shifts to the model selection process, highlighting the rationale behind the chosen analytical frameworks. All analyses and visualizations were conducted in R. Following this, robustness measures are presented, including a two-stage logistic regression model that incorporates climate variables to predict fish numbers and values. Additionally, a simplified model is provided to further validate the findings and ensure the reliability of the results.

4.1 Data

The data utilized in these analyses are derived from a variety of reputable sources, including the Food and Agriculture Organization (FAO), the Climate Prediction Center, the Composite Index of National Capabilities, Polity, and the Correlates of War. Additional data sources for teleconnections and fishery-related militarized disputes (MIDs) were also incorporated [insert sources for teleconnections and fishy mids]. The `peacesciencer` package in R was employed for the political control variables. All data were cleaned, coded, and merged using R and replication code for this process is available.

4.1.1 Dependent Variable: Fishery-Related MIDs

The dependent variable in this analysis is Fishery-Related Militarized Disputes (MIDs), which is binary coded to indicate the presence or absence of such disputes in a given dyad-year. A value of 1 signifies that an incident of militarized conflict related to fisheries occurred between the two countries in that dyad-year, while a value of 0 indicates the absence of a Fishery-Related MID. [Add Source]

4.1.2 Independent Variables

Our main independent variables, representing the fish catch stock and value for both the challenger and target states, are sourced from the FAO of the United Nations Fisheries and Aquaculture FishStat Database. The catch stock is quantified as Tonnes in kilograms (live weight), while the monetary value of the catch is expressed in terms of USD 1,000. To capture the dynamic nature of fish resource distribution, we calculate the percent change from the previous year for each of these values, allowing for an analysis of the shifts in both stock and value over time.

For our political and war variables, we draw on the work of Chen (2021) [14], which includes capital distance, contiguity, Correlates of War National Military Capabilities data, and regime type.[1]

Furthermore, we incorporate a set of climate-related controls, including the teleconnections of both target and challenger states to account for baseline climate exposure in each unit year. Additionally, we introduce an interaction term for the El Niño-Southern Oscillation (ENSO) Oceanic Niño Index (ONI) patterns, combined with a dummy variable for the South China Sea. This interaction captures the effects identified in previous literature [13] regarding the significance of ENSO patterns for fishery-related militarized disputes (MIDs) specifically in the South China Sea.

Each of these predictor variables was deemed significant based on the Gini coefficients of feature importance obtained from our random forest analysis. Consequently, we are confident in their inclusion in our models. Next, we will discuss our model specification.

4.2 Model Selection

For model selection, we first attempted a basic linear probability model; however, we found it to be inadequate and not a good fit for the data. Subsequently, we turned to a logistic regression model, which demonstrated a better fit and was therefore included in our main analysis. Additionally, we provide several alternative specifications of logistic regression models to ensure robustness in our findings.

4.2.1 Linear Probabilities Models (LPM)

The linear probabilities models are specified as follows:

$$\text{FishyMID}_{it} = \beta_0 + \beta_1 \cdot \text{ChallengerFishValue}_{it} + \beta_2 \cdot \text{TargetFishValue}_{it} + \alpha_i + \gamma_t + \epsilon_{it} \quad (1)$$

Equation 1 examines the relationship between fishery-related militarized disputes (FishyMID) and the fish value metrics for both the challenger and target states. Here, $\text{ChallengerFishValue}_{it}$ represents the monetary value of fish caught by the challenger state at time t, while $\text{TargetFishValue}_{it}$ denotes the corresponding value for the target state. The model includes fixed effects α_i to account for unobserved heterogeneity across individual dyads, as well as time fixed effects γ_t to control for temporal trends that may affect all dyads similarly. The error term ϵ_{it} captures the idiosyncratic shocks to the probability of conflict that are not explained by the included variables.

$$\text{FishyMID}_{it} = \beta_0 + \beta_1 \cdot \text{ChallengerFishNumber}_{it} + \beta_2 \cdot \text{TargetFishNumber}_{it} + \alpha_i + \gamma_t + \epsilon_{it} \quad (2)$$

[1] Chen (2021) also includes ATOP Defense alliances and major power indicators, and COW alliances; however, we exclude these controls due to our random forest feature importance analysis, which found them to be not significant.

Equation 2 follows a similar structure but focuses on the number of fish caught. In this model, $\text{ChallengerFishNumber}_{it}$ and $\text{TargetFishNumber}_{it}$ represent the quantities of fish caught by the respective states. Like the first model, it also incorporates dyad and time fixed effects and an error term to control for unobserved influences and variability in the data.

4.2.2 RESET Linearity Test Results

In conducting the RESET test for our linear regression model predicting FishyMIDs, we aimed to check for any potential specification errors that might indicate the need for higher-order terms or interactions that were not included in our original model (see Table 2). The tests yielded statistics of RESET = 3013.9 and 2848.3, suggesting strong evidence against the null hypothesis, which posits that our model is correctly specified. The p-values were found to be less than 2.2e-16, providing extremely strong evidence against the null hypothesis of correct model specification. This result indicates that our current linear specification may not adequately capture the relationships between our predictors and the outcome variable. Given these findings, we next explore the alternative specification of logistic regression and conduct further diagnostic tests to identify the best fit.

Table 2 RESET Test Results for LPM Models

Model	RESET Statistic	p value
LPM Fish Value	3013.9	¡ 2.2e-16
LPM Fish Number	2848.3	¡ 2.2e-16

Note: This table shows the RESET test results for the linear probability models specified in Equations 1 and 2. The models have 512,744 degrees of freedom, and both models have p-values less than 2.2e-16.

Although the linear probability models are not a strong fit, statistical significance indicates that an increase in the target fish value from the previous year is associated with a higher probability of fishery-related MIDs, as can be seen in Appendix A.

4.2.3 Logistic Regression Fit

After determining that the linear probability model specifications were not a good fit for our data, we next chose to estimate logistic regression models. Logistic regression is particularly suited for binary outcomes, as it estimates the probability that a given event occurs while overcoming some of the limitations inherent in linear probability models. In doing so, we estimate the following equations:

$$Pr(\text{FishyMID} = 1) = \frac{\exp(\beta_0 + \beta_1 \cdot \text{TargetFishValue} + \beta_2 \cdot \text{ChallengerFishValue})}{1 + \exp(\beta_0 + \beta_1 \cdot \text{TargetFishValue} + \beta_2 \cdot \text{ChallengerFishValue})} \quad (3)$$

Equation 3 models the probability of a fishery-related militarized dispute (FishyMID) occurring as a function of the monetary values of fish caught by both the target and challenger states. Here, β_0 represents the intercept, while β_1 and β_2 are coefficients that indicate the effect of changes in the target and challenger fish values, respectively, on the likelihood of disputes. The use of the exponential function ensures that the predicted probabilities lie between 0 and 1.

$$Pr(_{\text{FishyMID}} = 1) = \frac{_{\text{exp}}(\beta_0 + \beta_1 \cdot {}_{\text{TargetFishNumber}} + \beta_2 \cdot {}_{\text{ChallengerFishNumber}})}{1 + {}_{\text{exp}}(\beta_0 + \beta_1 \cdot {}_{\text{TargetFishNumber}} + \beta_2 \cdot {}_{\text{ChallengerFishNumber}})} \tag{4}$$

Equation 4 follows a similar structure but focuses on the number of fish caught. In this case, β_1 and β_2 represent the effects of the target and challenger fish counts on the probability of a fishery-related MID. Like the first model, it employs the logistic transformation to model the relationship, ensuring the predicted probabilities remain valid within the [0, 1] interval. This allows for a more interpretable and robust analysis of the factors contributing to fishery disputes.

4.2.4 Hosmer-Lemeshow Test Results

The Hosmer-Lemeshow test results for both models suggest that the logistic regression models fit the data well. For the fish value model, the test yields a p-value of 0.9989, and for the fish number model, it yields a p-value of 0.4421 (see Table 3). These high p-values indicate that there is no significant discrepancy between the observed and predicted event rates, which implies that the models are effectively capturing the relationship between the predictors and the outcome variable. In both cases, the models are based on logistic regression, which is appropriate for analyzing binary outcomes and assessing the influence of various predictors on the likelihood of the outcome occurring. The goodness-of-fit tests reinforce the reliability of these models in explaining the patterns observed in the data.

Table 3 Hosmer-Lemeshow Test Results

Model	χ^2	p value
Logit Fish Value	12.408	0.1339
Logit Fish Number	12.163	0.1441

Note: This table shows the results of the Hosmer-Lemeshow Test for the fit of the logistic regression models specified in Equations 3 and 4.

Given that this logistic regression model demonstrates a good fit for our data, it is employed in our main analysis. The results of this analysis can be observed in Table 1. Next, we move on to alternative model specifications for robustness.

4.3 Two-Stage Logistic Regression Model: Accounting for Climate-related Selection

Given that certain factors are expected to significantly influence fish distribution within a specific unit-year, we conduct a two-stage analysis for robustness. In the first stage, we predict the likelihood of fish value and numbers for both the target and challenger states based on climatological factors, including ONI ENSO (Oceanic Niño Index El Niño-Southern Oscillation) patterns and teleconnections. In the second stage, we incorporate these predicted fish catch value and count values into our existing logistic regression models to assess their impact on fishery-related militarized disputes.

4.3.1 Fish Number

In **Stage 1**, two linear regression models are employed to predict fish numbers for both the challenger and target countries. The *Predicted Challenger Fish Number* is estimated using a linear regression framework that incorporates environmental variables such as the ONI ENSOs and challenger teleconnection patterns. This is shown in Equation 5, specified by:

$$\text{Predicted Challenger Fish Number} = \beta_0+\beta_1\cdot\text{ONI ENSO}+\beta_2\cdot\text{Challenger Teleconnections}+\epsilon_1 \tag{5}$$

Similarly, the *Predicted Target Fish Number* model predicts the expected fish numbers for the target country, also based on the ONI ENSO and teleconnection patterns. Equation 6 is expressed as:

$$\text{Predicted Target Fish Number} = \beta_3+\beta_4\cdot\text{ONI ENSO}+\beta_5\cdot\text{Target Teleconnections}+\epsilon_2 \tag{6}$$

In **Stage 2**, the predicted fish numbers from Stage 1 are utilized in a logistic regression model to estimate the probability of a militarized dispute occurring, denoted as FishyMID = 1. The logistic regression framework allows for the modeling of a binary outcome based on the predicted fish numbers for both the challenger and target countries. Equation 7 shows the probability of a militarized dispute is given by:

$$Pr(\text{FishyMID} = 1) = \frac{\exp(\gamma_0 + \gamma_1 \cdot \text{Predicted Challenger Fish Number} + \gamma_2 \cdot \text{Predicted Target Fish Number})}{1 + \exp(\gamma_0 + \gamma_1 \cdot \text{Predicted Challenger Fish Number} + \gamma_2 \cdot \text{Predicted Target Fish Number})} \tag{7}$$

4.3.2 Fish Value

In **Stage 1**, two linear regression models are employed to predict fish values for both the challenger and target countries. The *Predicted Challenger Fish Value* is estimated using a linear regression framework that incorporates environmental variables such as the ONI ENSOs and challenger teleconnection patterns. This is shown in Equation 8, specified by:

$$\text{Predicted Challenger Fish Value} = \beta_0 + \beta_1 \cdot \text{ONI ENSO} + \beta_2 \cdot \text{Challenger Teleconnections} + \epsilon_1 \tag{8}$$

Similarly, the *Predicted Target Fish Value* model predicts the expected fish values for the target country, also based on the ONI ENSO and teleconnection patterns. Equation 9 is expressed as:

$$\text{Predicted Target Fish Value} = \beta_3 + \beta_4 \cdot \text{ONI ENSO} + \beta_5 \cdot \text{Target Teleconnections} + \epsilon_2 \tag{9}$$

In **Stage 2**, the predicted fish values from Stage 1 are utilized in a logistic regression model to estimate the probability of a militarized dispute occurring, denoted as FishyMID = 1. The logistic regression framework allows for the modeling of a binary outcome based on the predicted fish values for both the challenger and target countries. Equation 10 shows the probability of a militarized dispute is given by:

$$Pr(\text{FishyMID} = 1) = \frac{\exp(\gamma_0 + \gamma_1 \cdot \text{Predicted Challenger Fish Value} + \gamma_2 \cdot \text{Predicted Target Fish Value})}{1 + \exp(\gamma_0 + \gamma_1 \cdot \text{Predicted Challenger Fish Value} + \gamma_2 \cdot \text{Predicted Target Fish Value})} \tag{10}$$

The result tables of these model specifications for both fish value and fish number can be viewed in Appendix B. In short, both of these model specifications provide full robustness to our main findings, indicating that lower predicted fish values and numbers for challengers, along with higher predicted fish values and numbers for targets, lead to a higher probability of a fishery-related militarized dispute.

Overall, this two-stage modeling process effectively links environmental factors influencing fish populations to the likelihood of fishery-related disputes between countries.

4.4 Simplified Logistic Regression Models

It is prudent to show the results of the most simplified versions of the models for our variables of interest to provide a clear understanding of their individual effects. In Appendix C, we present the output for the simplified regression models, both with only the number and value variables as well as a set of models incorporating the teleconnections information. The results indicate that in both sets, a decline in the challenger fish value from the previous year remains statistically significant in leading to an increased probability of fishery-related militarized disputes (FishyMID). Although the other main coefficients do not meet conventional levels of statistical significance, their signs are consistent with those in the main models. These models correspond with Equations 3 and 4 above.

Supplementary information. If your article has accompanying supplementary file/s please state so here.

Acknowledgements. Acknowledgements are not compulsory. Where included they should be brief. Grant or contribution numbers may be acknowledged.

Declarations

Please check the Instructions for Authors of the journal to which you are submitting to see if you need to complete this section. If yes, your manuscript must contain the following sections under the heading 'Declarations':

- Funding
- Data availability
- Code availability
- Author contribution

References

[1] Perry, A.L., Low, P.J., Ellis, J.R., Reynolds, J.D.: Climate change and distribution shifts in marine fishes. Science **308**(5730), 1912–1915 (2005)

[2] Doney, S.C., Ruckelshaus, M., Emmett Duffy, J., Barry, J.P., Chan, F., English, C.A., Galindo, H.M., Grebmeier, J.M., Hollowed, A.B., Knowlton, N.: Climate change impacts on marine ecosystems. Annual review of marine science **4**(1), 11–37 (2012)

[3] Cheung, W.W., Sarmiento, J.L., Dunne, J., Frölicher, T.L., Lam, V.W., Deng Palomares, M., Watson, R., Pauly, D.: Shrinking of fishes exacerbates impacts of global ocean changes on marine ecosystems. Nature Climate Change **3**(3), 254–258 (2013)

[4] Dalby, S.: Climate change and geopolitics. In: Oxford Research Encyclopedia of Climate Science, (2017)

[5] Tol, R.S.: The economic impacts of climate change. Review of environmental economics and policy (2018)

[6] Arnell, N.W., Gosling, S.N.: The impacts of climate change on river flood risk at the global scale. Climatic Change **134**, 387–401 (2016)

[7] Li, Z., Fang, H.: Impacts of climate change on water erosion: A review. Earth-Science Reviews **163**, 94–117 (2016)

[8] Barange, M., Bahri, T., Beveridge, M., Cochrane, K.L., Funge-Smith, S., Poulain, F., *et al.*: Impacts of climate change on fisheries and aquaculture. United Nations' Food and Agriculture Organization **12**(4), 628–635 (2018)

[9] Spijkers, J., Singh, G., Blasiak, R., Morrison, T.H., Le Billon, P., Österblom, H.: Global patterns of fisheries conflict: Forty years of data. Global Environmental Change **57**, 101921 (2019)

[10] Zhang, H.: Fisheries cooperation in the south china sea: Evaluating the options. Marine Policy **89**, 67–76 (2018)

[11] Park, Y.K.: The role of fishing disputes in china–south korea relations. The National Bureau of Asian Research (NBR). https://map.nbr.org/2020/04/therole-of-fishing-disputes-in-china-south-korea-relations (2020)

[12] Mendenhall, E., Hendrix, C., Nyman, E., Roberts, P.M., Hoopes, J.R., Watson, J.R., Lam, V.W., Sumaila, U.R.: Climate change increases the risk of fisheries conflict. Marine Policy **117**, 103954 (2020)

[13] Hendrix, C.S., Glaser, S.M., Lambert, J.E., Roberts, P.M.: Global climate, el niño, and militarized fisheries disputes in the east and south china seas. Marine Policy **143**, 105137 (2022)

[14] Chen, F.R.: Extended dependence: Trade, alliances, and peace. The Journal of Politics **83**(1), 246–259 (2021)

Appendix A Linear Probabilities Model Results

Table A1 below shows the results from the Linear Probabilities Models as specified in Equations 1 and 2 above. While this model does not provide the best fit, it shows robustness that an increase in the target fish value is an important condition for the likelihood of Fishery MIDs.

Appendix B Two Stage Model Results

Table B2 corresponds to Equations 7 and 10 above and provides full robustness to our main findings. Specifically, it shows that lower predicted fish values and numbers for challengers, coupled with higher predicted fish values and numbers for targets, lead to a higher probability of a fishery-related militarized dispute.

Appendix C Simplified Model

These models correspond with Equations 3 and 4 above, but limit the use of control variables to show the most simplified effect. In Table C3, we find that a decline in the challenger fish value from the previous year remains statistically significant in leading to an increased probability of fishery-related militarized disputes. Although other main coefficients do not meet conventional levels of statistical significance, their signs are consistent with those in the main models.

Table A1 Linear Probability Models for Fishery Disputes

	Dependent variable: Fish Value Disputes	
	(1)	(2)
Challenger Change in Fish Value	0.008	
	(1.418)	
Target Change in Fish Value	0.025**	
	(0.012)	
Challenger Change in Fish Number		0.027
		(0.058)
Target Change in Fish Number		0.021
		(0.031)
ONI ENSO	0.0003	0.0003
	(0.0002)	(0.0002)
China Sea	0.0003***	0.0003***
	(0.0001)	(0.0001)
ONI ENSO X China Sea	0.002***	0.002***
	(0.0001)	(0.0001)
Challenger Total Capabilities	0.022***	0.022***
	(0.001)	(0.001)
Challenger Regime Type	0.002***	0.002***
	(0.001)	(0.001)
Target Regime Type	0.004***	0.004***
	(0.0002)	(0.0002)
Capital Distance	0.002***	0.002***
	(0.0002)	(0.0002)
Challenger Teleconnections	0.016***	0.016***
	(0.001)	(0.001)
Target Teleconnections	−0.00001**	−0.00001**
	(0.00000)	(0.00000)
Constant	0.00001**	0.00001**
	(0.00000)	(0.00000)
Observations	512,792	512,792
R^2	0.006	0.006
Adjusted R^2	0.006	0.006

Significance Levels: *p<0.1; **p<0.05; ***p<0.01
Note: Standard errors are clustered by dyad. Challenger coefficients for fish number and value have been scaled by 1×10^{26}, and target coefficients for fish number and value have been scaled by 1×10^{13} for clearer interpretation. Data sources and other variable transformations can be observed in the Methods section.

Table B2 Logistic Regression Results: Fish Value and Count Models

	Dependent variable: Fishy MID	
	(1)	(2)
Predicted Fish Value 1	-0.051**	
	(0.025)	
Predicted Fish Value 2	0.037***	
	(0.012)	
Predicted Fish Number 1		-0.019**
		(0.009)
Predicted Fish Number 2		0.014***
		(0.004)
ONI ENSO	-2.281	-0.570
	(3.916)	(1.711)
China Sea ES	1.732***	1.732***
	(0.447)	(0.447)
CINC1	16.231***	16.231***
	(2.698)	(2.698)
Polity 21	0.020	0.020
	(0.025)	(0.025)
Polity 22	0.065***	0.065***
	(0.023)	(0.023)
Capital Distance	-0.0002***	-0.0002***
	(0.0001)	(0.0001)
ONI ENSO: China Sea	-0.522	-0.522
	(0.403)	(0.403)
Constant	-12.691***	-10.576***
	(4.320)	(0.900)
Observations	532,640	532,640
Log Likelihood	-433.989	-433.989
Akaike Inf. Crit.	955.979	955.979

Significance Levels: *p<0.1; **p<0.05; ***p<0.01
Note: Standard errors are clustered by dyad. Factor variable Contiguity is not shown in this output. Challenger coefficients for fish number and value have been scaled by 1×10^{16}, and target coefficients for fish number and value have been scaled by 1×10^{6} for clearer interpretation. Data sources and other variable transformations can be observed in the Methods section.

Table C3 Logistic Regression Results: Simplified Models

	Dependent variable: Fishy MID			
2-5	(1)	(2)	(3)	(4)
Challenger Change in Fish Value	-0.000^{***}		-0.000	
	(0.000)		(0.000)	
Target Change in Fish Value	0.000		0.000	
	(0.000)		(0.000)	
Challenger Change in Fish Number		-0.000^{***}		-0.000
		(0.000)		(0.000)
Target Change in Fish Number		0.000		0.000
		(0.000)		(0.000)
Challenger Teleconnections			-1.515^{*}	-1.515^{*}
			(0.706)	(0.706)
Target Teleconnections			0.419	0.418
			(0.592)	(0.591)
Constant	-9.696^{***}	-9.697^{***}	-8.815^{***}	-8.814^{***}
	(0.803)	(0.802)	(1.134)	(1.134)
Observations	752,040	752,040	542,962	542,962
Log Likelihood	-759.569	-759.766	-676.854	-677.332
Akaike Inf. Crit.	1,583.138	1,583.532	1,421.708	1,422.663

Significance Levels: *p<0.05; **p<0.01; ***p<0.001

Note: Standard errors are clustered by dyad. Factor variable Contiguity is not shown in this output. Data sources and other variable transformations can be observed in the Methods section.