# Illuminating the Shadows: Assessing Compliance and Effectiveness in Marine Protected Areas with Satellite Imagery and AIS Data

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**Abstract**

Marine Protected Areas (MPAs) are an essential instrument for marine conservation, aimed at promoting the sustainable use of marine resources. In this study, I examine the dynamics and behavior of industrial fishing vessels in relation to MPAs, leveraging extensive global fishing data. I assess vessel compliance by evaluating their presence within MPAs, using both Automatic Identification System (AIS) data and satellite imagery. The main findings indicate that MPAs significantly reduce industrial fishing activity within their boundaries, with a more pronounced reduction observed in MPAs with higher levels of fishing protection. These findings hold true when using both satellite imagery and AIS data. Differences arise when focusing on Indonesia. In terms of biological conditions for fishing, those MPAs with more favorable fishing conditions tend to experience lower activity compared to other regions, highlighting their effectiveness in preserving these ecosystems. Additionally, evidence suggests that the COVID-19 pandemic led to significant increases in detected activity within MPAs. This research provides valuable insights for strengthening marine conservation efforts and enhancing MPA management by offering a deeper understanding of industrial fishing vessel behavior.

**Key words:** Marine Protected Areas, Fishing, Conservation Policy, Compliance.
**JEL Classification:** Q22, Q57, K42,

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# 1 Introduction

The depletion of marine resources has been a persistent concern in contemporary global biodiversity conservation debates and marine ecosystem preservation efforts (Herbert-Read et al., 2022, Lotze, 2021). Marine ecosystems have played a crucial role in combating global warming through carbon sequestration (Watson et al., 2020, DeVries et al., 2017) and regulating the planet's temperature (Griffis and Howard, 2013), as well as promoting sustainability that ensures food security (Ovando et al., 2023, Jefferson et al., 2022). However, sustainability in the use of these resources has not been a global characteristic. According to FAO (2022), the fraction of fishery stocks within biologically sustainable levels was 90% in 1974, but decreased to 64.5% by 2019. This decline is associated with the fact that 16 out of 18 FAO regions experience overfishing (Englander et al., 2023). These estimates, though concerning, may be even more alarming given that they are often considered to be underestimated (Pauly and Zeller, 2016, Watson and Pauly, 2001).

Marine Protected Areas (MPAs) have played a significant role in global conservation efforts by limiting human use and restricting extractive processes (Ward et al., 2022). These conservation tools have been implemented worldwide with the goal of promoting the protection of important habitats and ecosystems (Bank, 2006). MPAs have proven effective in restoring marine biodiversity and improving habitat quality (Roberts et al., 2001), increase the growth rate of fish populations (Rising and Heal, 2014), protecting endangered species (Pauly et al., 2002), and delivering a range of socioeconomic benefits associated with their successful implementation (Di Cintio et al., 2023, Rodríguez-Rodríguez et al., 2015).

According to UNEP-WCMC and IUCN (2021), by 2020, 7.7% of the global marine area was protected under the designation of MPAs, compared to only 0.5% in 2000. This rapid increase in recent years is due to the commitment of countries and international organizations to promote global conservation. The Convention on Biological Diversity's Aichi Target 11 called for designating 10% of marine areas as MPAs by 2020, later reinforced by Goal 14 ('Life Below Water') of the UN Sustainable Development Goals, and the recent proposal outlined in the Kunming-Montreal Global Biodiversity Framework, which urges countries to ensure that by 2030 at least 30% of coastal and marine areas are effectively conserved and managed (Andradi-Brown et al., 2023, Dinerstein et al., 2019).

MPAs have proven to be a crucial and effective conservation tool in preserving marine conservation objectives, particularly when properly implemented and managed (Ward et al., 2022, Edgar et al., 2014). However, their effectiveness is not solely guaranteed by their establishment; it heavily depends on effective administration, as well as robust monitoring and enforcement mechanisms, to ensure their success (Gill et al., 2017, Edgar et al., 2014). Ensuring that MPAs are adequately implemented is essential, given the growing concern over the rise of "paper parks"—protected areas that exist in name only, with minimal enforcement or management (Di Cintio et al., 2023, Rife et al., 2013). Such MPAs can undermine the credibility of marine protection efforts and may even impede the creation of additional MPAs if it appears that sufficient area expansion has already been achieved on paper (Di Cintio et al., 2023). The rapid increase in MPA designations has also generated tensions between conservation goals and the economic interests of fishery-dependent nations, as protecting biodiversity could potentially harm their economies (McDonald et al., 2024).

The significance of MPAs in promoting conservation, along with the various economic and environmental implications of their effectiveness, underscores the importance of ensuring that MPAs are truly meeting their intended purposes. Likewise, it highlights the need to transparently understand fishermen's behavior and identify the factors that contribute to the proper implementation of MPAs, ensuring they achieve their conservation objectives. For this reason, this study aims to evaluate the effectiveness of MPAs in regulating fishing activities within their boundaries on a global scale, using comprehensive and transparent data, to assess whether existing MPAs are fulfilling the conservation goals for which they were established.

In this paper, I evaluate the effectiveness of MPAs in reducing industrial fishing activity within their boundaries and analyze the behavior of vessels around Marine Protected Areas by utilizing vessel detection data from satellite imagery and Automatic Identification System (AIS) data. To achieve this, I employ causal inference techniques and econometric methods that allow me to capture the causal effect of MPAs on industrial activity at a global scale. I propose a regression discontinuity design that accounts for both observable and unobservable characteristics, which, if left unaccounted for, could introduce bias into the estimates. The identification strategy consists of comparing grid cells just inside and outside the MPA borders, exploiting the discontinuity associated with the boundaries of the protected areas[1].

Considering the richness of the data used, I also explore the heterogeneities driven by varying levels of fishing restrictions. Furthermore, to deepen our understanding of fishermen's motivations, I assess the relationship between industrial fishing activity within MPAs and observable characteristics such as distance to the shore, ports, and piracy events. Additionally, I examine the impact of the COVID-19 pandemic on fishermen's compliance and, finally, study the influence of biological conditions conducive to fishing on the decision-making processes of where fishermen choose to fish.

Based on the results, I can conclude that MPAs have been effective in reducing industrial fishing activity within their boundaries, despite some ongoing activity inside. Evidence of edge effects is found, where fishermen exploit the spillover benefits produced by the conservation of protected areas (Ziegler et al., 2022, Ohayon et al., 2021, Cuervo-Sánchez et al., 2018, Russ et al., 2003). The effectiveness of MPAs holds across all levels of fishing protection, with greater reductions in activity observed in areas with stricter restrictions, aligning with the existing literature Davis and Harasti (2020), Harasti et al. (2019), Sala and Giakoumi (2018), Advani et al. (2015), Miller and Russ (2014), Bergseth et al. (2013), Campbell et al. (2012).

[1]For similar analyses using this methodology, see Englander (2019) and Bonilla-Mejía and Higuera-Mendieta (2019).

I also find that a higher level of protection increases the likelihood of finding non-publicly tracked vessels. This is related to the fact that greater protection means a higher probability of being caught, so vessels will have greater incentives to turn off their transmitters in these areas to avoid detection.

I find that higher activity within MPAs is associated with shorter distances to the shore and greater distances from ports, suggesting that non-compliant fishermen prioritize minimizing travel costs over the likelihood of being apprehended, as enforcement tends to be more effective closer to shore (Albers et al., 2020). Additionally, fishermen are deterred by the presence of piracy. In regions with a history of piracy events, there is lower detection of industrial activity through AIS and higher detection through SAR, indicating that fishermen may disable their transmitters to avoid detection by pirates (Welch et al., 2022). However, no significant results are found to conclusively support this hypothesis.

Additionally, I find that the COVID-19 pandemic led to significant increases in detected activity within MPAs, likely due to reductions in enforcement funding and personnel (Smith et al., 2021). Finally, there is evidence that fishermen base their decisions on where to fish according to biological conditions conducive to fishing (Bos, 2021, Axbard, 2016, Flückiger and Ludwig, 2015). While MPAs do not necessarily encompass the areas with the most favorable biological conditions for fishing, those MPAs with better fishing conditions tend to experience lower activity compared to other areas, underscoring their effectiveness in conserving these ecosystems.

This article contributes to the literature in several ways. First, it provides empirical evidence through causal inference techniques regarding the global effectiveness of MPAs, using a comparable measure of levels of fishing protection across them. The findings support that MPAs with higher levels of protection yield better outcomes in terms of achieving their conservation objectives (Davis and Harasti, 2020, Harasti et al., 2019, Sala and Giakoumi, 2018, Advani et al., 2015, Miller and Russ, 2014, Bergseth et al., 2013, Campbell et al., 2012). Second, it advances the literature by utilizing a combination of AIS data and satellite imagery to provide the most transparent evidence possible on industrial fishing activity within MPAs, reducing the bias that might result from data manipulation in the assessment of MPA effectiveness (Pauly and Zeller, 2016, Watson and Pauly, 2001). And third, it contributes to the research on fisher compliance behavior (Bos, 2021, Diekert et al., 2021, Nøstbakken, 2008), by evaluating the impact of the COVID-19 pandemic and exploring how fishing conditions influence compliance among fishers.

The most closely related work to this study is a working paper by Burgess et al. (2019), which evaluates the global effectiveness of MPAs, analyzes the general equilibrium effect of MPAs on catch quantities and fish prices, and also proposes a theoretical model of the economics of conservation. Although this paper examines the same conservation instrument and uses some of the same Global Fishing Watch (GFW) data as in this study, there are key differences. First, I include data from satellite imagery in addition to AIS information, which can be manipulated by fishers (Welch et al., 2022). Second, I use a distinct database of protected areas, allowing for evidence focused on different levels of fishing protection. Third, I aim to explore potential factors explaining changes in fisher compliance, such as the impact of the COVID-19 pandemic and shifts in biological conditions favorable to fishing.

The findings of this article underscore the importance of utilizing increasingly reliable and accurate data to enhance the evaluation of conservation instruments, especially within the marine context. Misuse or lack of availability of data could lead to erroneous conclusions, potentially undermining the effectiveness of conservation objectives. Additionally, it highlights the importance of effective enforcement to ensure compliance with the conservation objectives of MPAs.

The rest of the article is organized as follows. Section 2 describes the data sources and presents descriptive statistics. Section 3 outlines the empirical model used. Section 4 presents the main results for MPAs, differentiating by levels of protection, and includes a case study on Indonesia along with an analysis of some potential determinants of fishing activity. In Section 5, I analyze the impact of the COVID-19 pandemic, and in Section 6, I examine fishing conditions. Finally, Section 7 concludes the article.

## 2 Data

Accurate and unbiased data are crucial for effective policy evaluation. This article examines fishing vessel compliance with regulations governing MPAs, emphasizing the need for data that prioritizes detection over fishing impacts. While much of the existing literature focuses on the effects of fishing activities—such as overexploitation—on marine ecosystems using stock and catch data (Marcos et al., 2021, Harasti et al., 2019, Gill et al., 2017, Ahmadia et al., 2015, Kelaher et al., 2015), these data sources are often limited and susceptible to manipulation (Pauly and Zeller, 2016, Watson and Pauly, 2001).

The growing availability of spatial data has greatly improved our understanding of global fishing dynamics (Paolo et al., 2024, Bos, 2021, Englander, 2019, Kroodsma et al., 2018). This data provides more reliable insights and extensive coverage, overcoming past limitations. However, not all data is equally resistant to manipulation. To evaluate the effectiveness of MPAs, this study uses two sources of fishing activity data, one more prone to manipulation than the other, to enhance reliability. The first source is data from Automatic Identification System (AIS) signals, which transmit vessel positions and help identify fishing activities and efforts (Kroodsma et al., 2018). The second is Synthetic Aperture Radar (SAR) from data sources like Sentinel, which identifies vessel locations, especially in coastal waters (Paolo et al., 2024). AIS data can be manipulated by disabling transmitters, limiting its reliability, while SAR data overcomes this issue and serves as an alternative to nighttime light data from VIIRS sensors, which are restricted to nighttime observations and affected by cloud cover (Hsu et al., 2019, Park et al., 2020).

For this study, I compiled a global database of ocean activity from both AIS and satellite data at a resolution of 0.1 degrees for the period 2017-2023. The dataset also includes climatic, biological, and biophysical information for each coastal grid[2].

### 2.1 AIS Fishing Activity Data

The Automatic Identification System (AIS) was originally designed to prevent vessel collisions by transmitting location, identity, speed, and heading to nearby ships. However, the use of AIS data has become increasingly important for monitoring fishing activity due to its ease of collection, accessibility, and comparability (Bos, 2021). After processing with machine learning techniques, AIS data allows for the prediction of vessel types and the number of fishing hours at each location with a resolution of 0.01 degrees (Kroodsma et al., 2018).

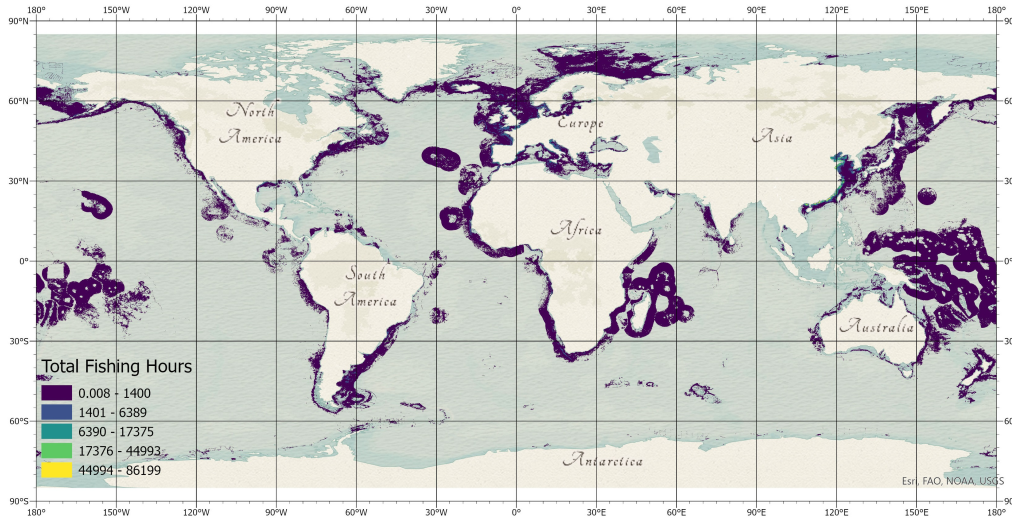
Figure 1 displays fishing efforts measured as the number of fishing hours by vessels within a given grid between 2017 and 2019 (Panel A) and the number of vessels detected (Panel B). Regions with higher detected fishing activity include Northern Europe, the East China Sea, the Australasian Pacific, and southern Africa around Madagascar. Conversely, areas with lower detected activity, possibly due to lower actual activity or under-detection via AIS data, include waters south of China, the territorial waters of Malaysia, Indonesia, and the Philippines, the Arabian Sea, the Gulf of Aden, and parts of Central America and the Caribbean. These regions, despite showing less activity, have a known history of significant fishing, suggesting under-detection rather than reduced activity.

### 2.2 SAR Fishing Activity Data

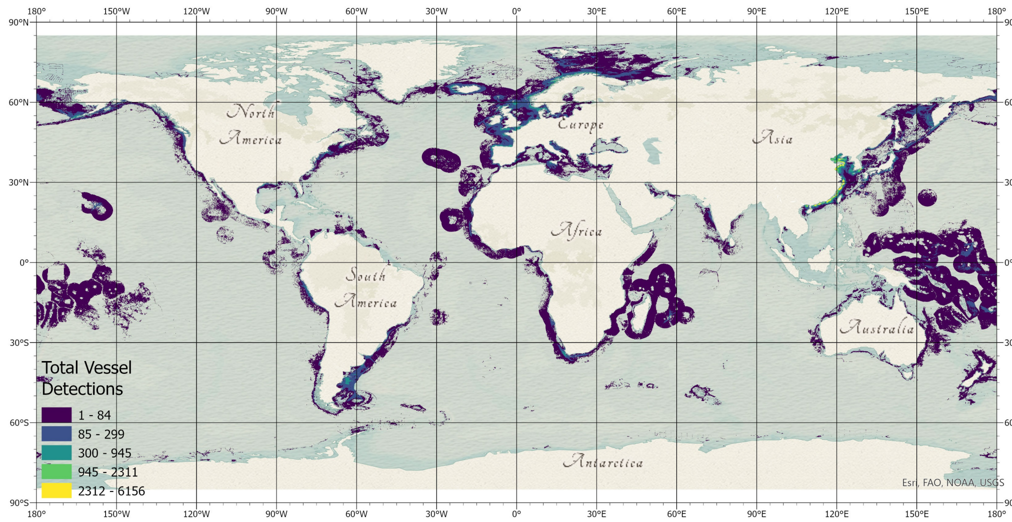
I employ data on industrial activity detected through the use of Synthetic Aperture Radar (SAR) imagery provided by Global Fishing Watch (GFW), which utilizes data from the Copernicus Sentinel-1 mission of the European Space Agency (ESA) (Paolo et al., 2024). This information allows me to obtain less manipulable data on the presence and activity within marine protected areas. While AIS data has been a major advancement in monitoring oceanic activity, the possibility of signal transmitters being altered or disabled makes measurements based on this information less reliable. The use of satellite imagery provides less manipulable data, enabling me to complement the evaluation of the dynamics of vessels within protected areas. Moreover, in comparison to the detection of vessels through nocturnal light sources, SAR imagery offers broader coverage, extending beyond nighttime activities.

Figure 2 illustrates the extent of industrial activity detected in global coastal areas during the 2017–2019 period. Panel A shows the tracked activity linked to Maritime Mobile Service Identities (MMSI), which are identifiers associated with AIS transmitters. In contrast, Panel

[2]Coastal waters refer to territorial waters within each country's Exclusive Economic Zones (EEZ).




*(a) Fishing Efforts*




*(b) Vessel detections*

Figure 1. Fishing activity using AIS data. Source: Authors' calculations based on data from GFW. Note: Observations are aggregated to a 1km resolution grid for each EEZ.

B depicts vessels detected without corresponding MMSI, meaning those vessels are not visible in publicly accessible AIS data. This concept is often referred to as "unseen vessels" (Welch et al., 2022).

When comparing Figure 1 and Figure 2, we can observe that SAR data complements the information on fishing activity derived from AIS data. Specifically, SAR data reveals additional information compared to AIS data in regions such as Indonesia, the Arabian Sea, and the Central Caribbean. Notably, there is a significant concentration of vessels not publicly tracked in Indonesia, where the least amount of AIS information is available.

One of the main limitations of SAR data is that its detection effectiveness is concentrated in coastal areas. While this is not an issue for my analysis, which focuses on global Exclusive Economic Zones (EEZs), no information is obtained for the EEZs of very small territories, such as Pacific islands. Additionally, the detection capacity is determined by the resolution of the images, approximately 20 meters for Sentinel-1, which prevents the detection of vessels smaller than 15 meters in length. As a result, this analysis focuses on industrial fishing, given the limitations in detecting artisanal fishing vessels, which also often lack AIS devices.

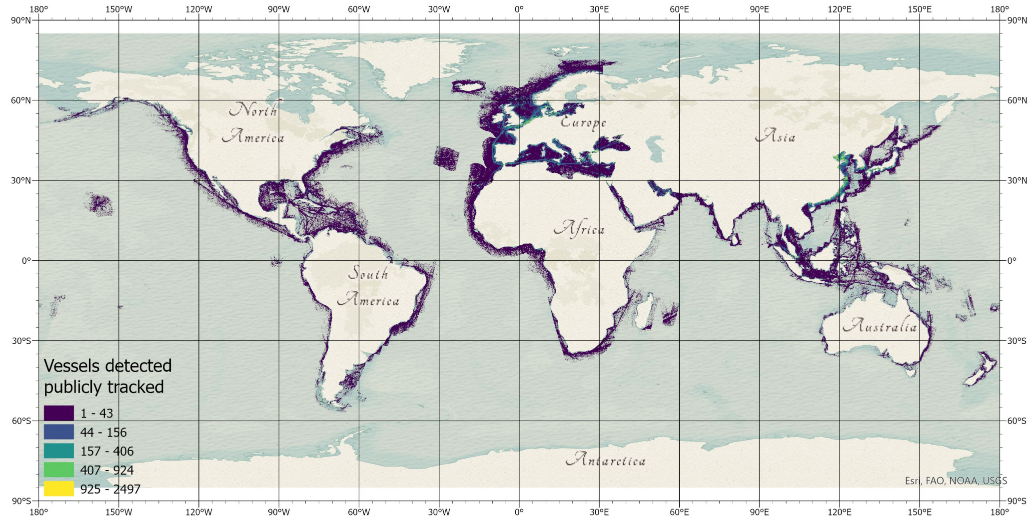
### 2.3 Comparing AIS Fishing Efforts and SAR vessels detections

The two databases utilized contain information on industrial activity at sea. The primary distinction between them lies in the potential for manipulation by fishers. In the case of AIS data, it is known that vessels have the ability to turn off their devices. In contrast, the information obtained from satellite imagery eliminates this manipulation bias, allowing for cleaner data on oceanic activity (Paolo et al., 2024).

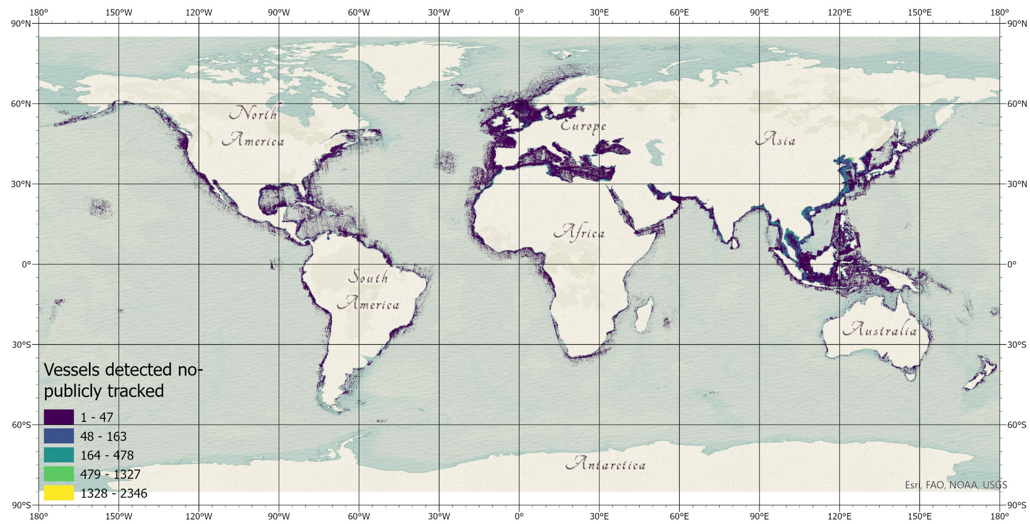
As previously mentioned, the combination of these two databases serves as complementary, enabling a more comprehensive analysis of vessel presence and, in turn, the effectiveness of MPAs on a global scale. Figure A1 shows the correlation between the two primary measures from AIS and SAR data, where a significant relationship between the two is observed. A 1% increase in the number of vessels detected via SAR is associated with a 0.13% increase in the estimated number of fishing hours derived from AIS data (Table A2), estimate that aligns with that obtained by Bos (2021) using VIIRS data in China.

### 2.4 Marine Protected Areas

The delimitation of the Marine Protected Areas was conducted using the Marine Managed Areas to Protect Marine Life database provided by ProtectedSeas. This dataset includes both federal and state-level data obtained through internet searches and downloads from official sources. In addition to providing the boundaries of the MPAs, this database allows me to obtain a comparable measure of the protection level of each MPA. I utilized a dataset as of 2023, focusing on MPAs stated in the dataset as established before 2017, which possess a WDPAID code and are located within Exclusive Economic Zones (EEZs). Figure 3 presents




***(a)*** *Vessels detected publicly tracked*




***(b)*** *Vessels detected no-publicly tracked*

Figure 2. Fishing activity using SAR data. Source: Authors' calculations based on data from GFW. Note: Observations are aggregated to a 1km resolution grid for each EEZ.

the map of the MPAs considered in the study (Panel A) and the coverage of protected areas within each EEZs (Panel B).

The significance of the ProtectedSeas database lies in its proposal of a specialized coding system for categorizing the restrictions related to fishing activity. This measure includes five categories: Least restrictive (=1), no known fishing restrictions; Less restrictive (=2), few species- or gear-specific restrictions apply; Moderately restrictive (=3), several species- or gear-specific restrictions apply, or either commercial or recreational fishing is entirely prohibited; Heavily restrictive (=4), fishing is mostly prohibited, with few exceptions; and Most restrictive (=5), fishing is completely prohibited.[3] When referring to fishing bans, it primarily pertains to artisanal fishing, as in principle, every MPA should restrict industrial fishing activity within its boundaries (Day et al., 2019). This system enables a more transparent and comparable characterization of the protection level of MPAs.

### 2.5 Climate and Environmental Variables

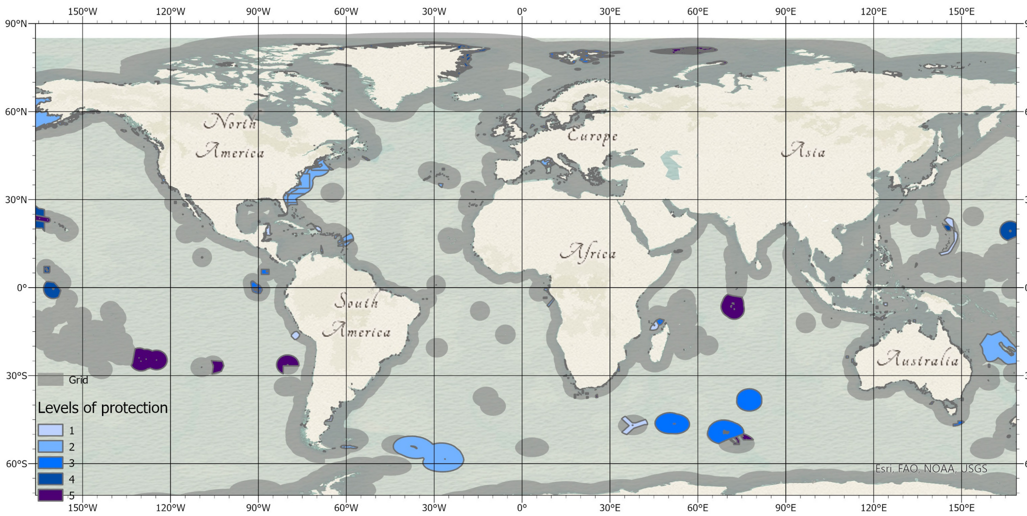
Finally, I include climatic and environmental variables as control variables. The data were compiled at the grid level with a resolution of 0.1 degrees, based on the data reported by MODIS Aqua Ocean Color Data (NASA Goddard Space Flight Center and Group, 2018). The environmental variables used are chlorophyll concentration and the phytoplankton absorption coefficient, in line with related literature (Bos, 2021, Axbard, 2016, Flückiger and Ludwig, 2015). Sea surface temperature is used as the climatic variable. No additional variables are considered due to the high likelihood of multicollinearity (Bos, 2021).

Figure 4 presents the distribution of environmental and climatic measures by grid for the period 2017–2019. Panel A shows the data for sea surface temperature, Panel B displays chlorophyll concentration, and Panel C presents the phytoplankton absorption coefficient rescaled to range between 0 and 100. These variables are used to characterize fishing conditions, which, according to biological literature, determine the favorable conditions for fishing productivity (Bos, 2021, Axbard, 2016, Flückiger and Ludwig, 2015). Table A3, Panel A, shows the relationship between this set of variables and the analysis variables.

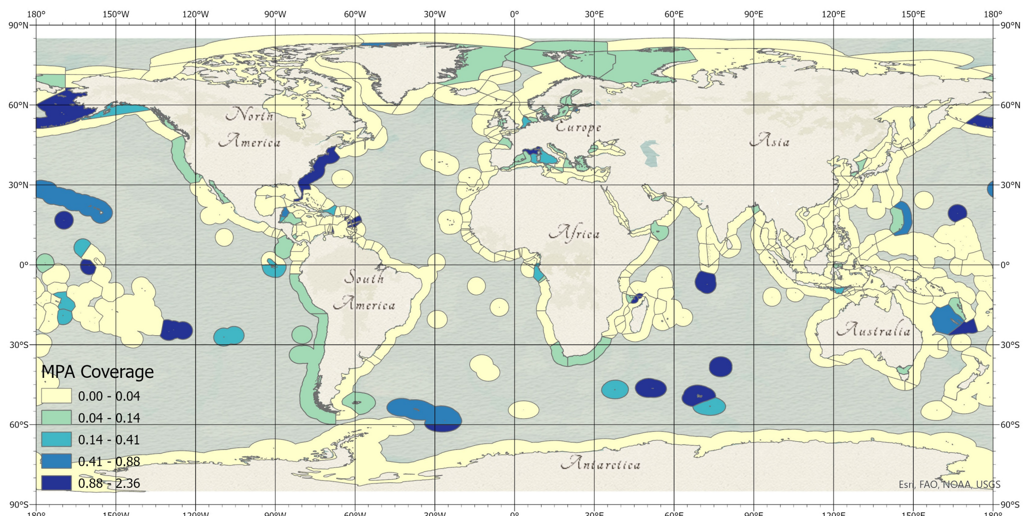
### 2.6 Descriptive Statistics

Table 1 presents the descriptive statistics of the main variables in dataset for the period 2017–2023. On average, 567.3 fishing hours per 1,000 $km^2$ per year were observed, with the presence of approximately 163 vessels. Based on SAR data, 114 publicly tracked vessels were detected per 1,000 $km^2$ per year, along with an average of 42 non-publicly tracked vessels. Additionally, the table provides descriptive statistics for environmental variables, including chlorophyll concentration and phytoplankton absorption (x100), as well as the climatic variable sea surface temperature, alongside time-invariant variables characterizing each grid in the

[3] For further details on the methodology, see ProtectedSeas Methodology

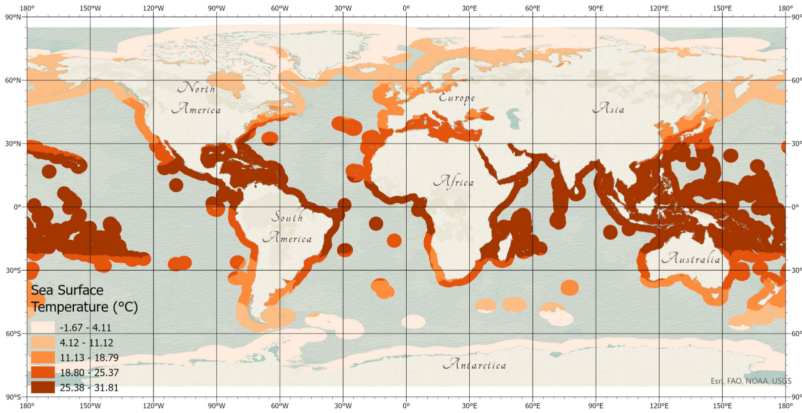



***(a)*** *Geography of Marine Protected Areas by levels of protection*

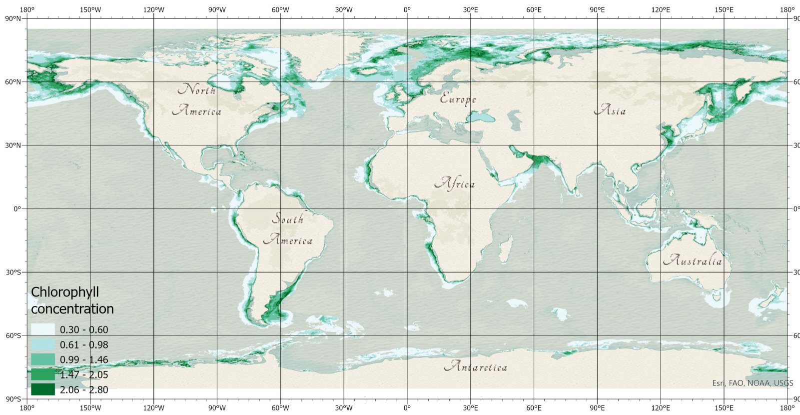



***(b)*** *Marine Protected Areas Coverage*

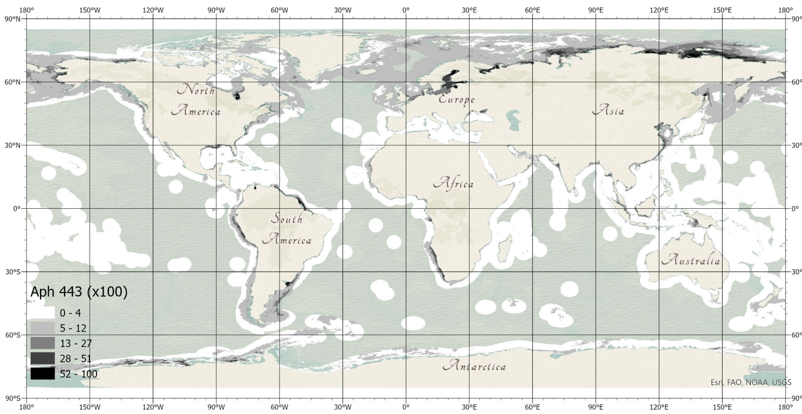
Figure 3. Marine Protected Areas Map. Source: Author, using information from Protected Seas and Marine Regions Repository. Note: The figure shows only MPA considered in this study.




*(a) Sea surface temperature*




*(b) Chlorophyll concentration*




*(c) Phytoplankton absorption coefficient*

Figure 4. climate and biological variables. Source: Authors' calculations based on data from MODIS and Marine Regions Repository. Note: Observations are aggregated to a 1km resolution grid for each EEZ.

dataset. Additional descriptive statistics for each protection level of the MPAs are presented in Table A1.

***Table 1:*** *Descriptive statistics*

| | N | Mean | Std.Dev | Min | 50% | Max |
|---|---|---|---|---|---|---|
| *Outcome variables* | | | | | | |
| Fishing Hours per 1000 $km^2$ | 2,904,545 | 567.3 | 4,718 | 0 | 4 | 611,666 |
| Vessels detection using AIS per 1000 $km^2$ | 2,904,545 | 162.9 | 548.9 | 8.13 | 45.05 | 52,231 |
| Vessels detection using SAR per 1000 $km^2$ | 1,732,572 | 114.3 | 423.9 | 0 | 19.23 | 26,325 |
| Unseen vessel detection using SAR per 1000 $km^2$ | 1,732,572 | 42.23 | 154.9 | 0 | 8.19 | 10,333 |
| Pr(Unseen vessel detection using SAR) | 1,732,572 | 0.54 | 0.50 | 0 | 1 | 1 |
| | | | | | | |
| *Environmental variables* | | | | | | |
| Sea surface temperature (°C) | 4,512,072 | 15.71 | 11.33 | -1.8 | 17.6 | 39 |
| Chlorophyll concentration | 2,590,634 | 0.82 | 1.99 | 0.001 | 0.26 | 83 |
| Phytoplankton absorption | 2,577,032 | 1.31 | 2.17 | 0 | 0.72 | 100 |
| | | | | | | |
| *Grid characteristics* | | | | | | |
| Distance to MPAs boundary (km) | 1,649,892 | 480 | 696 | -3,572 | -235 | 396 |
| Distance to Ports (m) | 1,649,892 | 669.1 | 918.8 | 0 | 326.4 | 4,740 |
| Distance to Shore (m) | 1,649,892 | 160.1 | 117.4 | 0 | 147 | 909 |
| Distance to Seamounts (m) | 1,649,892 | 324,319 | 393,675 | 77 | 158,283 | 2,651,093 |
| Distance to Pïracy events (m) | 1,649,892 | 1,907,882 | 1,677,618 | 381 | 1,463,816 | 6,416,163 |
| Depth (m) | 1,649,892 | -1,676 | 1,214 | -7,051 | -1,551 | -2 |

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: The observations refer to data from each 0.1-degree resolution grid. The grid characteristics variables are time-invariant, while the outcome and environmental variables correspond to the period from 2017 to 2023.

## 3 Empirical Model

A growing body of research has studied the effects of MPAs on conservation objectives. However, within the framework of analysis of this relationship, empirical difficulties arise related to the assignment of MPAs, which are not randomly assigned, but whose designation is determined by a series of observable variables. This means that comparisons between points located outside and inside the MPAs lead to biased estimates. Some works have attempted to deal with this identification problem using matching methods designed to strike a balance in the sample through the observed variables of the characteristics of ecosystems, oceans, and MPAs (Ahmadia et al., 2015, Gill et al., 2017). Although this method solves the problems conditional on the observable variables, it leaves out unobservable characteristics that are also determining factors and that can lead to bias in the estimates.[4] Other works have been conducted using other methodologies; however, these fail to capture causal effects (Harasti et al., 2019, Davis and Harasti, 2020).

[4] Additionally, for the analysis carried out here, there is not enough availability of variables with high resolution that are decisive in explaining why an area is designated as an MPA, which is necessary to be able to consider the application of matching methods such as Propensity Score Matching (PSM).

To deal with the endogeneity problem, the sample could be restricted to the closest observations to the MPA borders. To this end, the observations that are within an MPA will be taken as the treatment group, while the control group will consist of those cells just outside the MPA. Each cell counts information on industrial fishing activity (Table 1). The following spatial regression discontinuity is estimated, based on this information, to capture the causal effect of MPAs on fishing efforts:

$$\mathrm{Y}_i = \alpha + \tau_{RD_0} D_i + \sum_{k=1}^{k} \beta_k \Gamma_{ji}^k + D_i \sum_{k=1}^{k} \gamma_k \Gamma_{ji}^k + X_i + \mu_i \tag{1}$$

Where $Y_{ji}$ denotes the fishing activity outcome variable at a given grid, denoted by $i$. $D_i$ is an indicative variable that takes the value of 1 if the observation is inside the MPA or 0 if it is outside. The variable $\Gamma_i$ indicates the minimum distance to the MPA border by the centroid grid. Controls such as depth, sea surface temperature, Chlorophyll concentration, Phytoplankton absorption coefficient, distance to the shore, distance to ports, distance to piracy events, and distance to seamounts $X_i$ are included, and it is also controlled by a polynomial of order $k$ of the distance to the MPA border.

The effect is estimated using the model proposed by Calonico et al. (2014), which selects the optimal bandwidth and computes the conditional mean difference between cells located inside (treatment) and outside (control) of protected areas. To assess the robustness of the estimates, I re-estimate the model using three approaches: the optimal bandwidth, a fixed bandwidth of 50 km (which, on average, represents 12.6% of the maximum distance within the MPAs), and a donut hole approach that excludes a 2 km buffer zone around the MPA borders. The parameter of interest, $\tau_{RD_0}$, captures the average effect on global fishing activity per 1,000 $km^2$ per year during the study period 2017 - 2019.

The main assumption of the model is that confounders vary smoothly at the cutoff, which I test using the permutation test of continuous distribution of covariates proposed by Canay and Kamat (2018). The results of this test are presented in Table 2. Most tests fail to reject the null hypothesis of continuously distributed covariates at the cutoff, suggesting that the results obtained through the use of regression discontinuity can be considered causal.[5]

# 4 Results

Table 3 presents the results of the estimation of the effect of MPAs on industrial fishing activity, measured using AIS data. For each outcome variable, estimates are provided using the optimal bandwidth, fixed bandwidth, and the donut hole approach. Additionally, conventional, bias-corrected, and robust estimates as proposed by Calonico et al. (2014) are reported. While my preferred specification is the conventional estimate with optimal bandwidth, the

[5]The results for MPAs with protection levels of 1 and 3 should be interpreted with caution, as the joint test rejects the null hypothesis of continuously distributed covariates at the cutoff.

***Table 2:*** *Continuous distribution of baseline marine characteristics at MPAs borders*

| | Treatment | | Control | | Permutation test | |
|---|---|---|---|---|---|---|
| | *Mean* | *Std.Dev* | *Mean* | *Std.Dev* | *t-test* | *p-value* |
| **A. Levels of protection = 1** | | | | | | |
| Sea surface temperature (°C) | 19.33 | 0.08 | 19.3 | 0.013 | 0.16** | 0.01 |
| Chlorophyll concentration | 1.33 | 0.046 | 0.88 | 0.004 | 0.03 | 0.48 |
| Phytoplankton absorption | 1.27 | 0.031 | 1.21 | 0.003 | 0.05 | 0.22 |
| Depth (m) | -1,615 | 9.39 | -1,630 | 1.28 | 0.02 | 0.61 |
| Joint test | | | | | 0.16** | 0.03 |
| **B. Levels of protection = 2** | | | | | | |
| Sea surface temperature (°C) | 11.26 | 0.033 | 13.79 | 0.015 | 0.04 | 0.35 |
| Chlorophyll concentration | 1.2 | 0.01 | 1.11 | 0.004 | 0.04 | 0.36 |
| Phytoplankton absorption | 1.71 | 0.008 | 1.79 | 0.006 | 0.04 | 0.27 |
| Depth (m) | -1,656 | 2.75 | -1,621 | 1.13 | 0.06 | 0.18 |
| Joint test | | | | | 0.06 | 0.47 |
| **C. Levels of protection = 3** | | | | | | |
| Sea surface temperature (°C) | 10.38 | 0.038 | 16.03 | 0.02 | 0.08 | 0.08 |
| Chlorophyll concentration | 0.55 | 0.012 | 0.805 | 0.005 | 0.05 | 0.17 |
| Phytoplankton absorption | 1.14 | 0.01 | 1.35 | 0.006 | 0.04 | 0.25 |
| Depth (m) | -1,204 | 3.29 | -1,651 | 1.52 | 0.2*** | 0.001 |
| Joint test | | | | | 0.2** | 0.01 |
| **D. Levels of protection = 4** | | | | | | |
| Sea surface temperature (°C) | 20.59 | 0.053 | 16.38 | 0.02 | 0.05 | 0.21 |
| Chlorophyll concentration | 0.21 | 0.007 | 0.668 | 0.004 | 0.11** | 0.03 |
| Phytoplankton absorption | 0.45 | 0.005 | 1.12 | 0.005 | 0.13** | 0.02 |
| Depth (m) | -2,227 | 4.38 | -1,943 | 1.37 | 0.02 | 0.71 |
| Joint test | | | | | 0.13 | 0.08 |
| **E. Levels of protection = 5** | | | | | | |
| Sea surface temperature (°C) | 21.78 | 0.04 | 12.28 | 0.016 | 0.04 | 0.29 |
| Chlorophyll concentration | 0.304 | 0.014 | 0.687 | 0.003 | 0.02 | 0.53 |
| Phytoplankton absorption | 0.622 | 0.006 | 1.19 | 0.004 | 0.02 | 0.79 |
| Depth (m) | -1,861 | 3.54 | -1,593 | 1.18 | 0.01 | 0.87 |
| Joint test | | | | | 0.04 | 0.78 |

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Columns 1,2, 3 and 4 present the descriptive statistics of cells of the nearest MPA boundary. The last two columns presents the test statistic and p-value of the Canay and Kamat (2018) permutation test of continuous distribution of covariates at the cutoff.

other estimates are included for the sake of transparency, and because in the analysis by protection levels, the donut hole approach appears to provide more accurate estimates due to the concentration of activity near the border. According to the results, MPAs reduce fishing effort within their boundaries by 316.54 hours per 1,000 $km^2$/year. Similarly, the number of detected vessels decreases by 181.09 vessels per 1,000 $km^2$/year.

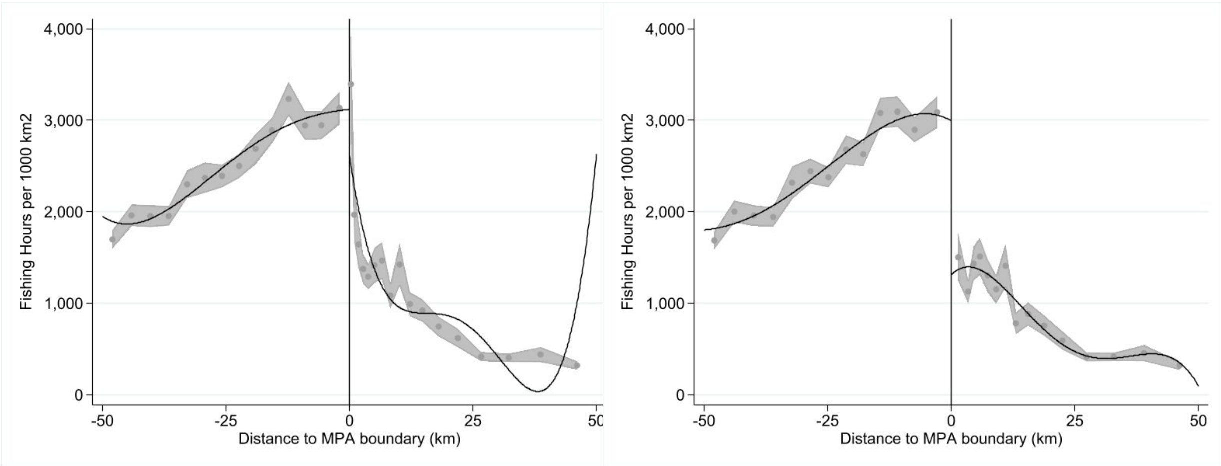
To validate the sensitivity of the results, I estimate the regressions for bandwidths ranging from 5km to 50km, and the coefficients are consistent and remain negative (Figure A8). Additionally, as an extra robustness check, I run the regressions using a placebo for the MPA boundary, and it is observed that the negative and significant effect is concentrated around the true cutoff point (Figure A9).

***Table 3:*** *Regression discontinuity effect of MPAs on Fishing activity using AIS data*

| | *Fishing Hours per 1000 $km^2$* | | | *Vessels detection using AIS per 1000 $km^2$* | | |
|---|---|---|---|---|---|---|
| | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Conventional | -316.54** | -537.79*** | -377.93** | -181.09*** | -258.91*** | -284.14*** |
| | (147.57) | (74.62) | (184.38) | (30.04) | (13.05) | (29.49) |
| Bias-corrected | -320.13** | -307.02*** | -333.15* | -169.18*** | -249.91*** | -278.24*** |
| | (147.57) | (74.62) | (184.38) | (30.04) | (13.05) | (29.49) |
| Robust | -320.13* | -307.02*** | -333.15 | -169.18*** | -249.91*** | -278.24*** |
| | (184.18) | (113.04) | (221.19) | (32.75) | (19.83) | (36.26) |
| Bandwidth (km) | 15.33 | 50 | 12.09 | 10.65 | 50 | 17.31 |
| Observations | 71,506 | 411,042 | 67,710 | 71,506 | 411,042 | 67,710 |

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. Fishing hours is expressed in $hours/km^2$per1000. Calonico et al. (2014) RD estimate used with optimal bandwidth (columns 1, and 4), fixed 50 kms bandwidth (columns 2, and 5), and 2km donut hole approach (columns 3, and 6). All regressions control for the climatic, physical and biological variables. I present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

Figure 5 illustrates the findings, showing that, on average, fishing activity increases near the borders and decreases significantly within the MPAs. The increase in fishing activity along the edges of MPAs has been well documented in the literature (Ohayon et al., 2021, Cuervo-Sánchez et al., 2018, Russ et al., 2003), and in many cases, this pattern does not emerge until more than seven years after the implementation of MPAs (Ziegler et al., 2022). This explains the findings of McDonald et al. (2024), whose results suggest that MPAs do not displace fishing efforts in the early years following their establishment. Meanwhile, the fishing activity detected within the MPAs follows a strategic pattern, with effort decreasing as the distance into the protected area increases. This suggests that fishers weigh the potential benefits of fishing inside the MPAs against the likelihood of being caught, which increases with greater distances, as they require more time to exit the area. This dynamic is observed across most of the outcome variables analyzed and for various levels of protection, with the effect being more pronounced in MPAs with lower levels of protection (Figure 6).




***(a)*** *Fishing hours* ***(b)*** *Fishing hours: Donut hole 2km*

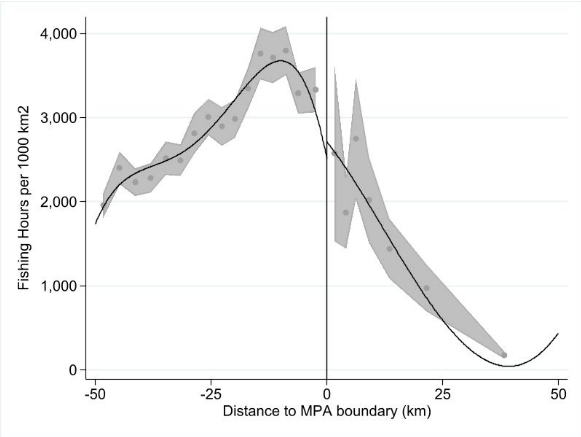
Figure 5. Regression discontinuity effect of MPAs on fishing activity using AIS data

Table 4 presents the results for AIS data across different protection levels of MPAs. I observe that, regardless of the protection level, most MPAs successfully reduce fishing activity within their boundaries. In terms of fishing effort, the magnitude of the effect increases as the level of protection of the MPAs increases. Figure 6 visually illustrates this relationship for fishing efforts. Figures A2 shows the RD plot for vessel detections. In terms of the number of vessels detected, it appears visually evident that an increase in the level of fishing protection leads to a greater reduction in fishing activity. However, in the estimations that include controls, no significant effects are found to support this evidence.

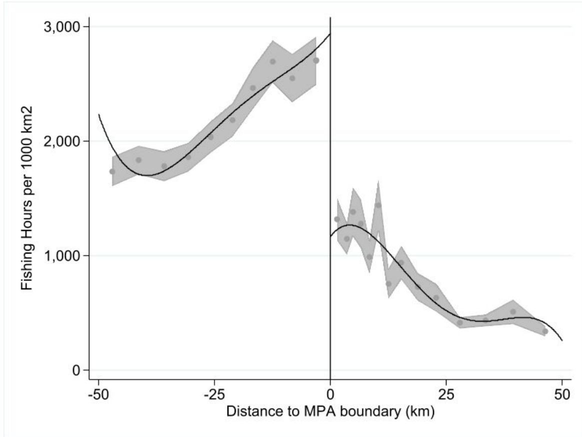
***Table 4:*** *Regression discontinuity effect of MPAs on Fishing activity using AIS data by levels of protection*

| | *Fishing Hours per 1000 km²* | | | *Vessels detection using AIS per 1000 km²* | | |
|---|---|---|---|---|---|---|
| | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | | | *Level of protection = 1* | | | |
| Conventional | -191.6 | -443.3* | -58.70 | -183.9** | -369.5*** | -325.4*** |
| | (418.7) | (249.1) | (573.4) | (72.38) | (35.97) | (78.85) |
| Bias-corrected | -186.1 | -194.2 | 52.76 | -154.2** | -344.7*** | -299.7*** |
| | (418.7) | (249.1) | (573.4) | (72.38) | (35.97) | (78.85) |
| Robust | -186.1 | -194.2 | 52.76 | -154.2* | -344.7*** | -299.7*** |
| | (510.4) | (343.3) | (702.3) | (79.44) | (51.45) | (94.71) |
| bandwidth (km) | 15.07 | 50 | 11.21 | 10.91 | 50 | 16.08 |
| Observations | 22,005 | 116,923 | 20,859 | 22,005 | 116,923 | 20,859 |
| | | | *Level of protection = 2* | | | |
| Conventional | -435.4** | -520.2*** | -991.1*** | -169.4*** | -105.0*** | -204.1*** |
| | (179.8) | (108.9) | (330.3) | (37.75) | (17.78) | (50.17) |
| Bias-corrected | -434.9** | -444.3*** | -1,091*** | -171.6*** | -144.5*** | -222.8*** |
| | (179.8) | (108.9) | (330.3) | (37.75) | (17.78) | (50.17) |
| Robust | -434.9** | -444.3*** | -1,091*** | -171.6*** | -144.5*** | -222.8*** |
| | (214.7) | (157.7) | (384.6) | (45.65) | (27.56) | (57.9) |
| bandwidth (km) | 17.68 | 50 | 12.98 | 13.21 | 50 | 13 |
| Observations | 24,667 | 106,616 | 23,083 | 24,667 | 106,616 | 23,083 |
| | | | *Level of protection = 3* | | | |
| Conventional | 5.71 | -316.5** | 504.7 | 23.3 | -92.21*** | 92.54 |
| | (268.8) | (133.3) | (380.5) | (25.62) | (13.57) | (68.22) |
| Bias-corrected | 90.7 | 40.88 | 666.8* | 31.46 | -9.60 | 122.7* |
| | (268.8) | (133.3) | (380.5) | (25.62) | (13.57) | (68.22) |
| Robust | 90.7 | 40.88 | 666.8 | 31.46 | -9.60 | 122.7* |
| | (331.9) | (210.0) | (420.4) | (29.66) | (18.62) | (73.15) |
| bandwidth (km) | 16.70 | 50 | 9.45 | 9.91 | 50 | 6.44 |
| Observations | 11,390 | 59,411 | 10,765 | 11,390 | 59,411 | 10,765 |
| | | | *Level of protection = 4* | | | |
| Conventional | -176.1 | -476.6*** | -452.0 | -282.3*** | -257.2*** | -271.7** |
| | (219.9) | (126.6) | (392.0) | (79.6) | (45.23) | (118.6) |
| Bias-corrected | -143.8 | -115.1 | -468.8 | -302.8*** | -299.5*** | -295.2** |
| | (219.9) | (126.6) | (392.0) | (79.6) | (45.23) | (118.6) |
| Robust | -143.8 | -115.1 | -468.8 | -302.8*** | -299.5*** | -295.2** |
| | (259.9) | (175.1) | (486.0) | (97.54) | (72.49) | (148.7) |
| bandwidth (km) | 12.81 | 50 | 12.7 | 20.11 | 50 | 16.32 |
| Observations | 6,342 | 65,922 | 6,127 | 6,342 | 65,922 | 6,127 |
| | | | *Level of protection = 5* | | | |
| Conventional | -1,422* | -577.4*** | -955.3* | 31.59 | -23.03 | -83.27 |
| | (783.2) | (221.5) | (560.1) | (116.6) | (52.04) | (101.9) |
| Bias-corrected | -1,647** | -744.6*** | -1,165** | 62.74 | -24.70 | -79.56 |
| | (783.2) | (221.5) | (560.1) | (116.6) | (52.04) | (101.9) |
| Robust | -1,647* | -744.6*** | -1,165* | 62.74 | -24.70 | -79.56 |
| | (950.3) | (395.8) | (669.4) | (150.1) | (90.08) | (133.1) |
| bandwidth (km) | 10.68 | 50 | 11.53 | 17.55 | 50 | 17.8 |
| Observations | 7,101 | 62,162 | 6,875 | 7,101 | 62,162 | 6,875 |

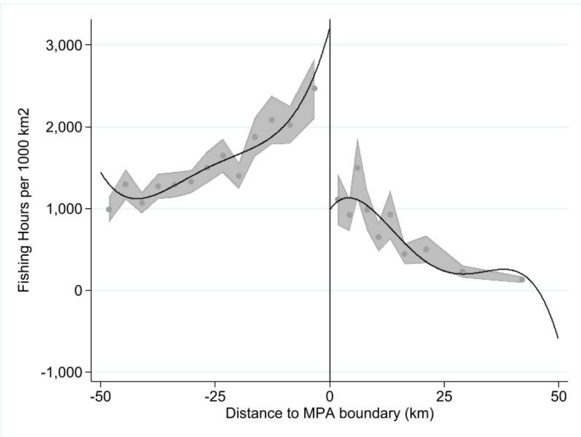
Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. Fishing hours is expressed in $hours/km^2$per1000. Calonico et al. (2014) RD estimate used with optimal bandwidth (columns 1, and 4), fixed 50 kms bandwidth (columns 2, and 5), and 2km donut hole approach (columns 3, and 6). All regressions control for the climatic, physical and biological variables. I present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.



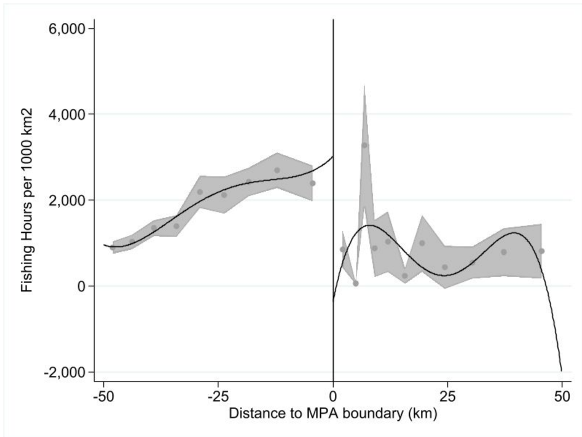

***(a)*** *Level 1*



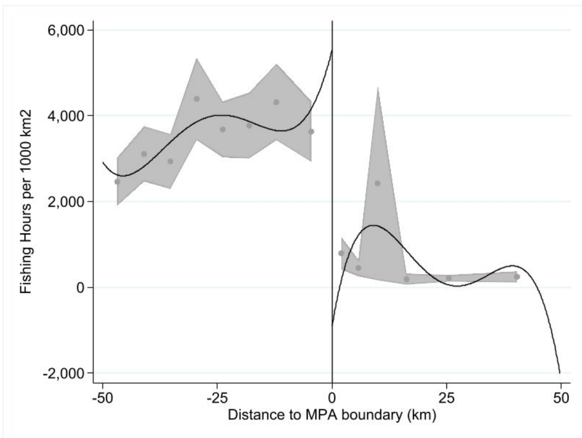

***(b)*** *Level 2*




***(c)*** *Level 3*




***(d)*** *Level 4*




***(e)*** *Level 5*

Figure 6. Regression discontinuity effect of MPAs on fishing activity using AIS data by levels of protection. Note: All graphs present the estimates following the donut hole approach with a 2km exclusion zone.

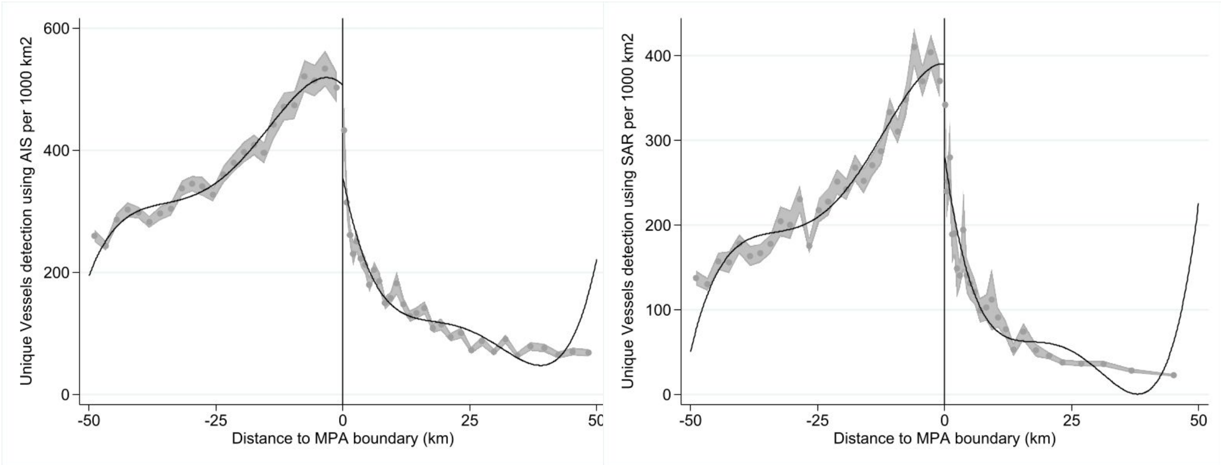
When comparing the data from AIS and SAR, I observe a complementarity in the analysis.

The patterns described by AIS and SAR data are similar. Figure 7 illustrates how vessel detection behaves for both data sources. In levels, on average, there is a greater reduction in activity using AIS data (Table 3) compared to the reduction estimated using SAR data (Table 5). For different protection levels, SAR data shows that the number of vessels decreases sharply near the border, with this reduction being significantly greater in MPAs with higher levels of protection (-276.5), compared to those with lower protection levels, -189.4 and -118.6 for protection levels 2 and 1, respectively (Table A4). Figures A3 display the RD plots for vessels detected using SAR.

***Table 5:*** *Regression discontinuity effect of MPAs on Fishing activity using SAR data*

| | *Vessels detection using SAR per 1000 km$^2$* | | |
|---|---|---|---|
| | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* |
| | (1) | (2) | (3) |
| Conventional | -60.56** | -135.44*** | -162.68*** |
| | (23.58) | (9.87) | (25.52) |
| Bias-corrected | -51.57** | -134.57*** | -168.52*** |
| | (23.58) | (9.87) | (25.52) |
| Robust | -51.57** | -134.57*** | -168.52*** |
| | (25.64) | (13.65) | (30.85) |
| Bandwidth (km) | 6.49 | 50 | 15.33 |
| Observations | 49,531 | 160,238 | 46,299 |

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. Calonico et al. (2014) RD estimate used with optimal bandwidth (columns 1, and 4), fixed 50 kms bandwidth (columns 2, and 5), and 2km donut hole approach (columns 3, and 6). All regressions control for the climatic, physical and biological variables. I present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.




***(a)*** *Vessel detection: AIS* ***(b)*** *Vessel detection: SAR*

Figure 7. Regression discontinuity effect of MPAs on fishing activity comparing AIS and SAR data

For vessels not publicly tracked using SAR data, I observe that, in general, MPAs have been effective in reducing this type of "in the dark" activity (Park et al., 2020). Table 6 presents the results for the number of no-publicly tracked vessels and the likelihood of encountering such vessels. The estimates for the number of no-publicly tracked vessels are robust, indicating that MPAs have reduced this activity by approximately 15 vessels per $km^2$/year. However, when assessing the probability of finding at least one no-publicly tracked vessels within MPAs, I find that it increases by approximately 0.17 percentage points (pp), though this estimate is not robust across different specifications.

Figure 8 shows the RD plots for no-publicly tracked vessels, while Table A4 presents the estimates for each protection level. Figures A4 and A5 display the RD plots for the number of detected vessels and its probability for each protection level, respectively. In terms of probability, it is observed that a higher level of protection increases the likelihood of finding non-publicly tracked vessels. This is related to the fact that greater protection means a higher probability of being caught, so vessels will have greater incentives to turn off their transmitters in these areas to avoid detection. Additionally, note that within MPAs, the dispersion of the data is considerably higher compared to the data outside the MPA (Figure A5)

### 4.0.1 Indonesia case

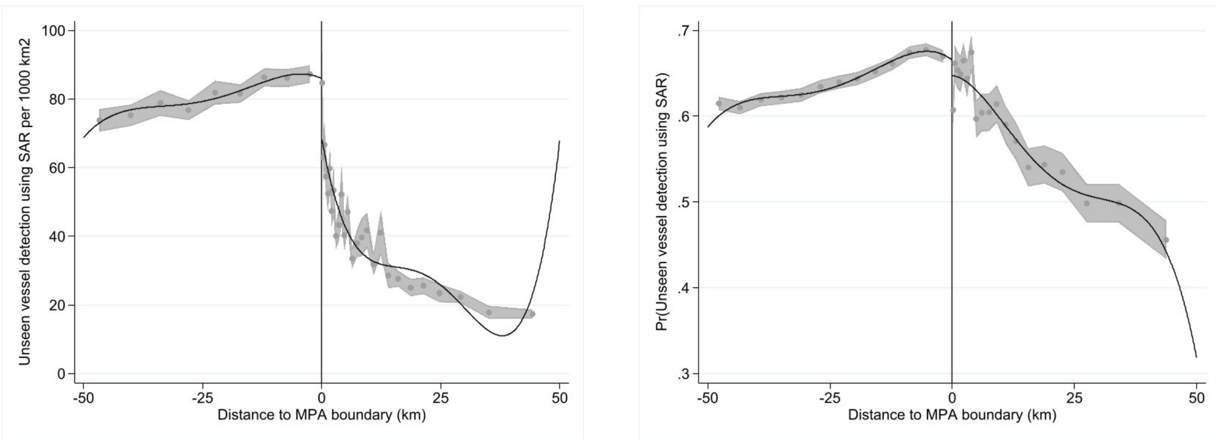
In general terms, no significant differences are observed when using AIS and SAR data. However, when focusing on Indonesia, it becomes clear that this region represents a hotspot for the detection of vessels not publicly tracked (Welch et al., 2022), and it is also the area with the lowest AIS detection rates (Figure 1).

Figure 9 compares the detection of the number of vessels using AIS and SAR around MPAs in Indonesia. Using AIS, we could conclude that activity within the MPAs is very low;

***Table 6:*** *Regression discontinuity effect of MPAs on vessels detected No-Publicly tracked using SAR data*

| | *Unseen vessel detection using SAR per 1000 km$^2$* | | | *Pr(Unseen vessel detection using SAR)* | | |
|---|---|---|---|---|---|---|
| | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Conventional | -14.6*** | -16.43*** | -19.36*** | 0.01 | 0.012 | 0.17*** |
| | (3.10) | (1.69) | (3.54) | (0.017) | (0.009) | (0.036) |
| Bias-corrected | -14*** | -14.66*** | -19.37*** | 0.009 | 0.002 | 0.18*** |
| | (3.10) | (1.69) | (3.54) | (0.017) | (0.009) | (0.036) |
| Robust | -14*** | -14.66*** | -19.37*** | 0.009 | 0.002 | 0.18*** |
| | (3.64) | (2.44) | (4.27) | (0.02) | (0.012) | (0.042) |
| Bandwidth (km) | 13.68 | 50 | 15.87 | 8.69 | 50 | 7.66 |
| Observations | 49,531 | 160,238 | 46,299 | 49,531 | 160,238 | 46,299 |

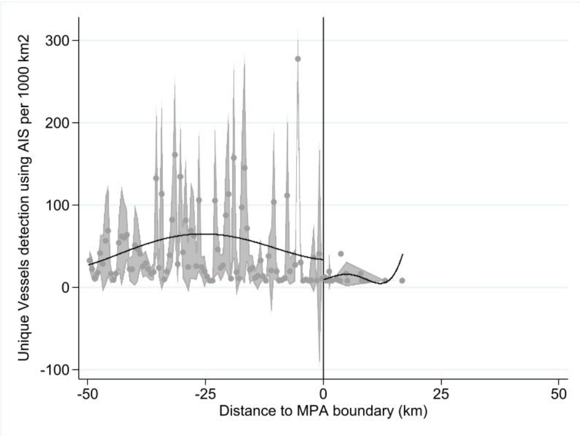
Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. Calonico et al. (2014) RD estimate used with optimal bandwidth (columns 1, and 4), fixed 50 kms bandwidth (columns 2, and 5), and 2km donut hole approach (columns 3, and 6). All regressions control for the climatic, physical and biological variables. I present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.



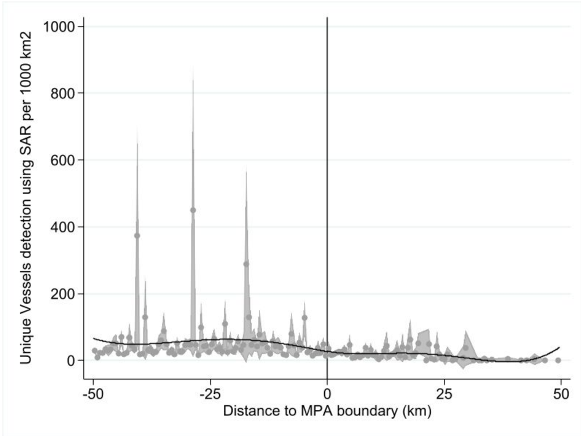

***(a)*** *Unseen Vessel detection*

***(b)*** *Pr(Unseen Vessel detection)*

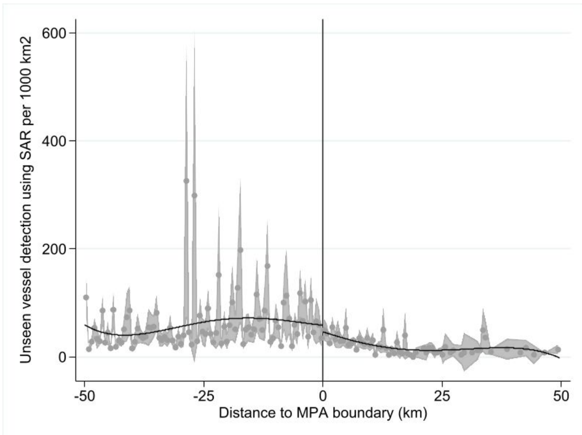
Figure 8. Regression discontinuity effect of MPAs on unseen vessels detected using SAR data




***(a)*** *Vessel detection: AIS*




***(b)*** *Vessel detection: SAR*




***(c)*** *Vessels detected no–publicly tracked: SAR*

Figure 9. Regression discontinuity effect of MPAs on fishing activity comparing AIS and SAR data in Indonesia

***Table 7:*** *Regression discontinuity effect of MPAs on fishing activity comparing AIS and SAR data in Indonesia*

| | *Vessels detection using AIS per 1000 $km^2$* | | | *Vessels detection using SAR per 1000 $km^2$* | | | *Unseen vessel detection using SAR per 1000 $km^2$* | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Conventional | 116.6*** | -58.02** | -108.0 | -8.16 | -35.93*** | 25.19 | -33.42** | -34.25*** | -169.4*** |
| | (37.56) | (29.46) | (73.54) | (16.94) | (12.34) | (33.91) | (16.40) | (10.81) | (56.23) |
| Bias-corrected | 191.4*** | 15.85 | -1,110*** | -3.96 | -28.94** | 11.09 | -37.2** | -42.76*** | -192.4*** |
| | (37.56) | (29.46) | (73.54) | (16.94) | (12.34) | (33.91) | (16.40) | (10.81) | (56.23) |
| Robust | 191.4*** | 15.85 | -1,110 | -3.96 | -28.94* | 11.09 | -37.2* | -42.76*** | -192.4*** |
| | (50.35) | (60.63) | (1,787) | (20.48) | (15.69) | (36.62) | (19.35) | (16.04) | (60.14) |
| Bandwidth (km) | 5.43 | 50 | 15.36 | 9.85 | 50 | 6.31 | 16.22 | 50 | 8.16 |
| Observations | 226 | 2,410 | 217 | 1,552 | 8,651 | 1,413 | 1,552 | 8,651 | 1,413 |

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. Calonico et al. (2014) RD estimate used with optimal bandwidth (columns 1, 5 and 7), fixed 50 kms bandwidth (columns 2, 6 and 8), and 2km donut hole approach (columns 3, 7 and 9). All regressions control for the climatic, physical and biological variables. I present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

however, when using SAR data, we observe a significantly different picture. Table 7 presents the estimates for Indonesia. There is no consistency in the results obtained using AIS and SAR data. Using the optimal bandwidth, the detected activity increases significantly when using AIS data, while with SAR data, no statistically significant effect is found, which would suggest that MPAs are not effective in controlling fishing activity. However, when using the fixed bandwidth, significant reductions in detected activity are observed, which are more pronounced in terms of the activity of non-publicly tracked vessels.

### 4.1 Law Enforcement and Marine Conservation

Part of the effectiveness of MPAs is determined by the capacity of organizations to enforce regulations through monitoring, control, and surveillance of protected areas (Gill et al., 2017). It is well known that these capacities are not uniform across marine territories, especially when influenced by factors such as political and economics factors between countries, as well as the distance from shore and ports, which can hinder the ability of institutions to enforce regulations.

One of the factors I analyze here is maritime piracy, which is associated with political instability, lack of capacity, geography, and economic marginalization (Galgano, 2024), all of which can jeopardize the conservation objectives of MPAs. Additionally, I examine the relationship between distance to the shore and ports, which reflects the capacity of authorities to enforce regulations (Edgar et al., 2014, Advani et al., 2015). However, it is also possible that greater distance increases costs for fishermen, discouraging activity in more remote MPAs, and that piracy may further dissuade fishing activities.

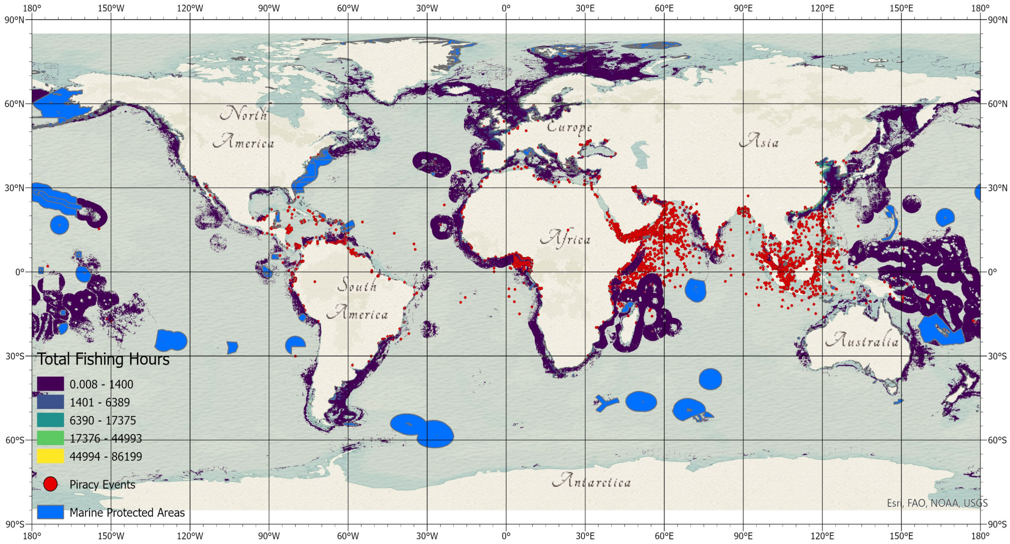



Figure 10. Piracy events and fishing activity

Figure 10 displays global patterns of pirate activity and fishing efforts. It shows that regions with lower fishing activity, as detected by AIS, tend to correspond with areas where piracy events are more frequent. Table A3, Panel B, presents the regression results for distance-related variables on various outcome measures within MPAs. While most estimates have small magnitudes and lack statistical significance, it is notable that both distance to the shore and to ports decrease fishing activity within MPAs. This suggests that rather than reduced enforcement driving this effect, it is the less incentives related to fishing in more remote and often less productive areas that prevail (Burgess et al., 2019).

However, when evaluating the probability of detecting non-publicly tracked vessels within MPAs, distance to ports is associated with an increased probability, while distance to the shore reduces it. A potential explanation is that remote MPAs farther from the shore involve higher travel costs, whereas distance to ports does not necessarily imply isolation, where the lower likelihood of enforcement may dominate.

Regarding proximity to pirate incidents, piracy tends to deter industrial fishing in areas with higher prevalence or risk of piracy, rather than encouraging it due to perceived lower enforcement from authorities. These findings should be interpreted as informative, not causal. Future research should aim to establish causality in this relationship.

## 5 The COVID-19 impacts

The COVID-19 pandemic had a significant impact on most economic and social sectors globally. There is evidence that the pandemic altered the ways in which society interacted with the environment. In this section, I aim to assess the pandemic's impact on compliance with regulations within MPAs. To do so, I propose estimating a difference-in-discontinuity regression model.

The proposed specification follows the structure presented in Wang et al. (2023). A local linear regression is employed within a given bandwidth around the MPA boundaries, controlling for the distance to the boundary variable. The purpose of this model is to estimate the effect of the pandemic on industrial activity within MPAs, calculated as the difference in the discontinuity before and after the pandemic (post-2020).

$$y_{it} = \alpha_{0t} + \alpha_{10} D_i + \alpha_{11} D_i \times Post_t + \alpha_{2t} \Gamma_i + \alpha_{3t} D_i \times \Gamma_i + \gamma_i + \delta_t + \epsilon_{it} \text{ if } |\Gamma_i| \leq h$$

Where $D_i$ is a binary indicator variable that takes the value of 1 if the grid is within an MPA, and 0 otherwise. $Post_t$ follows the rule $\mathbb{1}\{\text{Year} \geq 2020\}$. The variable $\Gamma_i$ indicates the minimum distance to the MPA border by the centroid grid. Fixed effects for grid and year are included, denoted by $\gamma_i$ and $\delta_t$, respectively. The bandwidth is denoted by $h$, and regressions are run for arbitrarily assigned bandwidths of 50 km and 10 km around the boundary. One limitation of this specification is that the assignment rule is consistent for both pre- and post-pandemic periods, which could introduce bias. However, given that the boundary is assumed to be fixed, this is not expected to introduce the level of noise that would typically arise under the methodology's assumptions.

***Table 8:*** *Estimations for the RD-DiD: Effect of COVID-19 pandemic on industrial activity in MPAs*

| | *Vessels detection using SARper 1000 km²* | | *Unseen vessel detection using SAR per 1000 km²* | |
|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* |
| post20=1 x inside=1 | 26.97** | 22.68* | 11.01*** | 7.64** |
| | (12.79) | (12.47) | (3.06) | (3.42) |
| Bandwidth (km) | 50 | 10 | 50 | 10 |
| Observations | 522,761 | 145,248 | 522,761 | 145,248 |

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. All estimates were conducted with year and grid fixed effects for the period 2017–2023. Robust standard errors are in parentheses.

Table 8 presents the estimation results for the proposed specification across all outcome variables. The estimates are for the period 2017–2023. The results indicate that, following the pandemic, although average activity decreased (Figure A6), the average activity within MPAs increased (Table 8). This outcome can be explained by the reductions in funding and personnel caused by the economic and social shock generated by the pandemic (Smith et al., 2021). The lack of resources hindered the enforcement, monitoring, and surveillance of these protected areas, contributing to an increase in unauthorized activity within their boundaries (Gill et al., 2017).

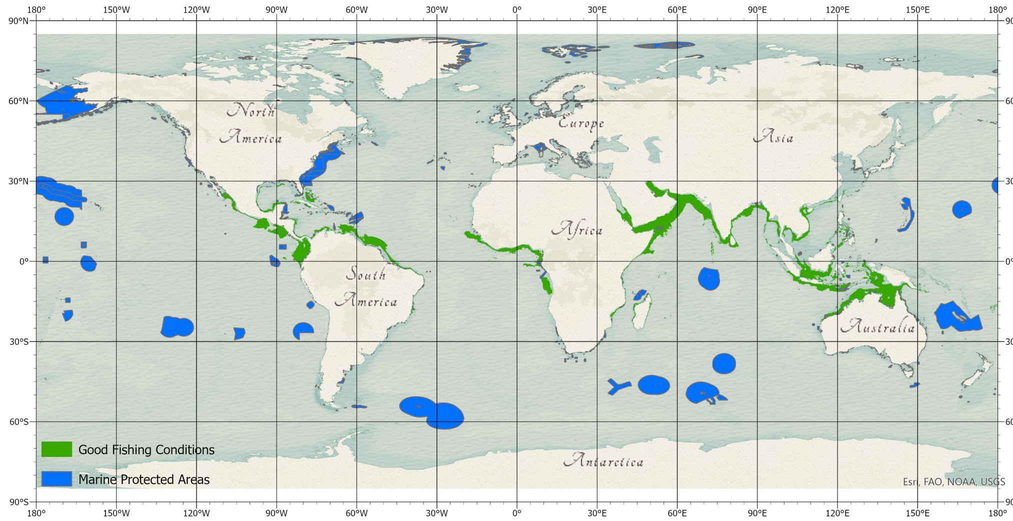
## 6 Fishing Conditions and Compliance

In order to assess the fishing conditions that determine the opportunities available to fishers, I utilize oceanographic data derived from geospatial information to calculate a measure of fishing conditions following the approach of Axbard (2016). The measure incorporates data on chlorophyll-a concentration and sea surface temperature, consistent with the marine biology literature (Semedi and Hadiyanto, 2013). Chlorophyll-a concentration is linked to the amount of phytoplankton, which forms the base of the ocean food web and serves as the primary food source for small pelagic fish. Sea surface temperature, on the other hand, influences the development and survival of fish eggs as well as the distribution and migration of fish (Axbard, 2016). Based on this information, areas with favorable fishing conditions are identified using the following equation:

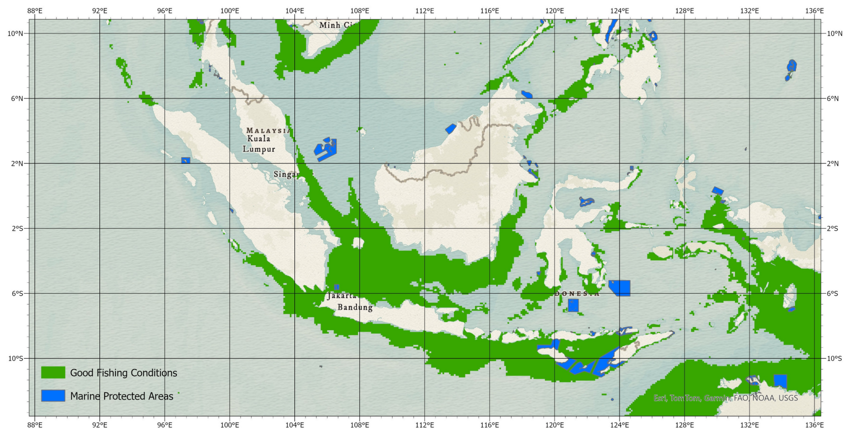
$$f_i = \mathbb{1}\{26 \leq SST_i \leq 30 \wedge 0.3 \leq chlorophyll_i \leq 2.8\}$$

Where $\mathbb{1}\{\}$ is an indicator function that takes the value of 1 when the information in grid $i$ meets the condition proposed by Semedi and Hadiyanto (2013) and evaluated by Axbard (2016). This approach approximates the identification of areas with optimal fishing conditions. Additionally, the approach proposed by Bos (2021) and Flückiger and Ludwig (2015) will be considered. They propose to use the phytoplankton absorption coefficient at 443 nm as a baseline measure to evaluate fishing conditions, with higher phytoplankton presence indicating better fishing conditions.

Figure 11 displays the areas with favorable fishing conditions according to Axbard (2016). Panel A shows the global distribution, while Panel B presents the distribution in Indonesia, which is one of the hotspots for the measure of fishing conditions. Figure 12 indicates that, on average, there is no significant difference in the probability of finding areas with favorable fishing conditions at the boundary of the MPAs. However, it is generally observed that conditions outside the MPAs are more favorable than those inside, aligning with the findings of Burgess et al. (2019), who argue that MPAs are located in more remote and less productive waters. Regarding the approach proposed by Bos (2021) and Flückiger and Ludwig (2015), Figure 3, Panel C presents the distribution of phytoplankton concentration.




***(a)*** *Global*




***(b)*** *Indonesia*

Figure 11. Areas with good fishing conditions and MPAs. Note: Fishing conditions are calculated based on sea surface temperature and chlorophyll concentration (Axbard, 2016).

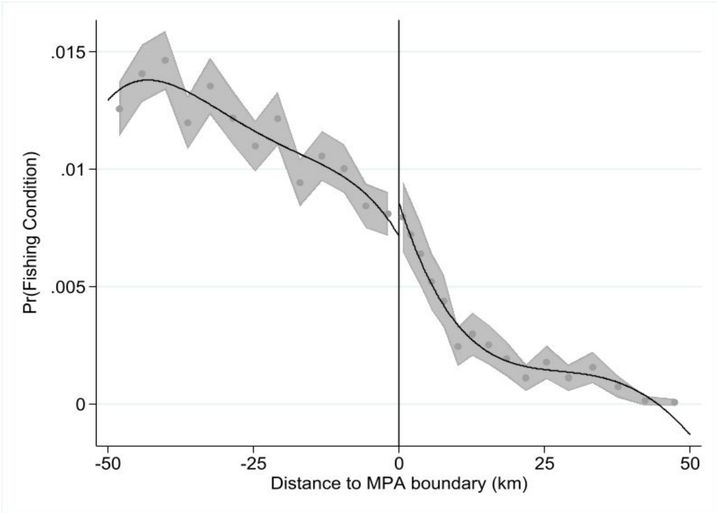



Figure 12. Rdplot Fishing Condition

To assess the impact of fishing conditions on fishing activity within MPAs, I propose estimating a fixed effects model as follows:

$$y_{it} = \beta FishingCondition_{it} + \alpha D_i + \pi FishingCondition_{it} \times D_i + \gamma_i + \theta_t + \epsilon_{it}$$

Where $FishingCondition_{it}$ is the variable calculated using the formula proposed by Axbard (2016) or based on phytoplankton concentration as suggested by Bos (2021) and Flückiger and Ludwig (2015). $D_i$ is an indicator variable that takes the value of 1 if grid i is within an MPA, and 0 otherwise. Fixed effects for time and grid, $\theta_t$ and $\gamma_i$, respectively, are included. The parameter of interest is $\pi$, which captures the effect of fishing conditions within the MPAs.

Table 9 presents the results of the effect of fishing conditions on industrial activity within MPAs. Panel A displays the results based on the approach proposed by Flückiger and Ludwig (2015) and Bos (2021), while Panel B shows the findings using the method from Axbard (2016). The estimations are performed across different time periods to assess robustness. Consistent with previous literature, favorable fishing conditions increase fishing activity (Panel B), although the opposite is observed for publicly tracked vessels in Panel A. However, for non-publicly tracked vessels, in both cases, better conditions and higher phytoplankton concentrations lead to an increase in the number of detected vessels.

When assessing the impact of these conditions within MPAs, I find that most estimates indicate lower activity within MPAs compared to outside, implying that, even though MPAs may not necessarily represent the areas with the best biological conditions for fishing, those MPAs with favorable fishing conditions still exhibit reduced activity relative to other areas. This demonstrates their effectiveness in conserving these ecosystems.

***Table 9:*** *Effect of fishing conditions on industrial activity inside MPAs*

| | *Vessels detection using SAR per 1000 km$^2$* | | | *Unseen vessel detection using SAR per 1000 km$^2$* | | | *Pr(Unseen vessel detection using SAR)* | | |
|---|---|---|---|---|---|---|---|---|---|
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* | *(8)* | *(9)* |
| *Panel A* | | | | | | | | | |
| aph 443 (x100) | -3.06 | 1.87 | 1.31 | 4.12*** | 3.56*** | 2.23*** | -0.0007 | 0.001 | 0.0002 |
| | (2.21) | (1.35) | (1.45) | (0.88) | (0.61) | (0.62) | (0.002) | (0.00) | (0.002) |
| aph 443 (x100) x 1.Inside | 1.26 | 5.76 | 10.08 | -0.93 | -3.42*** | -1.32 | 0.027*** | 0.013* | 0.013* |
| | (3.02) | (7.33) | (9.61) | (1.38) | (0.96) | (0.94) | (0.01) | (0.007) | (0.008) |
| Sample | 2017-2019 | 2017-2023 | 2017-2019, 2021-2023 | 2017-2019 | 2017-2023 | 2017-2019, 2021-2023 | 2017-2019 | 2017-2023 | 2017-2019, 2021-2023 |
| Observations | 72,856 | 263,296 | 203,816 | 72,856 | 263,296 | 203,816 | 72,856 | 263,296 | 203,816 |
| *Panel B* | | | | | | | | | |
| 1.fishing Condition | 1.40 | -3.32*** | -4.55*** | -1.50** | 5.74*** | 5.56*** | 0.009*** | 0.006*** | 0.005** |
| | (0.85) | (0.65) | (0.71) | (0.75) | (0.59) | (0.64) | (0.003) | (0.002) | (0.002) |
| 1.fishing Condition x 1.Inside | -2.18 | 6.88*** | 5.68*** | 3.55 | -2.66* | -2.16 | 0.005 | -0.007 | -0.01 |
| | (2.42) | (2.02) | (2.14) | (3.84) | (1.58) | (1.82) | (0.027) | (0.016) | (0.018) |
| Sample | 2017-2019 | 2017-2023 | 2017-2019, 2021-2023 | 2017-2019 | 2017-2023 | 2017-2019, 2021-2023 | 2017-2019 | 2017-2023 | 2017-2019, 2021-2023 |
| Observations | 673,293 | 1,661,606 | 1,396,616 | 673,293 | 1,661,606 | 1,396,616 | 673,293 | 1,661,606 | 1,396,616 |

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. All estimates were conducted with year and grid fixed effect. Robust standards errors in parentheses.

As shown in Figures 11, 12 and A7, favorable fishing conditions do not necessarily occur within MPAs. This can be explained by the fact that in many cases, the designation of MPAs is not primarily aimed at conserving specific fish species but rather at preserving biodiversity, which does not always include commercially valuable fish (Andradi-Brown et al., 2023).

## 7 Conclusions

This paper evaluates the effectiveness of MPAs in reducing industrial fishing activity on a global scale. To achieve this, I utilize data from satellite imagery and AIS to gather information on fishing effort and the number of publicly and non-publicly tracked vessels at a resolution of 0.1 degrees. I propose a Regression Discontinuity model that addresses selection bias issues by controlling for observable and unobservable characteristics, allowing for causal estimates. Using this model, I estimate the reduction in fishing activity within MPAs according to the level of fishing protection. Additionally, to gain deeper insight into fishers' motivations, I examine the impact of disruptive shocks, such as those caused by the COVID-19 pandemic, and the effect of biological fishing conditions on fishing decisions.

The results indicate that MPAs have been effective in reducing industrial fishing activity within their boundaries, particularly in MPAs with higher levels of protection. These findings hold true when using both satellite imagery and AIS data. Differences arise when focusing on Indonesia, a region characterized as a hotspot for non-publicly tracked vessels (Paolo et al., 2024). I find that a higher level of protection increases the likelihood of finding non-publicly tracked vessels. This is related to the fact that greater protection means a higher probability of being caught, so vessels will have greater incentives to turn off their transmitters in these areas to avoid detection. It is also found that, on average, fishing activity increases near the borders of MPAs, providing empirical evidence of a positive spillover effect. Although the establishment of new MPAs typically does not displace activity to surrounding waters (McDonald et al., 2024), it is known that despite the reduction in the area available for fishing, protected areas generate increased biomass and greater long-term benefits for fishing activity due to this spillover effect, which explains the observed increase in activity near the borders (Ziegler et al., 2022, Cuervo-Sánchez et al., 2018). Additionally, the study finds that fishermen are deterred by the presence of piracy, and higher levels of non-publicly tracked activity within MPAs are associated with shorter distances to shore and greater distances from ports. This suggests that non-compliant fishermen prioritize minimizing travel costs over the likelihood of being apprehended.

Furthermore, I find that the COVID-19 pandemic led to significant increases in detected activity within MPAs, likely due to reductions in enforcement funding and personnel (Smith et al., 2021). Finally, there is evidence that fishermen base their decisions on where to fish according to biological conditions conducive to fishing (Bos, 2021, Axbard, 2016, Flückiger and Ludwig, 2015). While MPAs do not necessarily encompass the areas with the most favorable biological conditions for fishing, those MPAs with better fishing conditions tend to experience lower activity compared to other areas, underscoring their effectiveness in conserving these ecosystems.

Some limitations of this study are primarily related to the data. One limitation involves the measurement of the fishing effort variable, which is reported by GFW as a prediction, serving as an estimate of the apparent number of fishing hours. Another limitation is associated with the possible detection of non-fishing vessels in the SAR data, particularly for non-publicly tracked vessels. However, there is no reason to believe that non-fishing vessels would have incentives to enter an MPA for activities other than fishing with the motivation of avoiding detection. The main concern would be an overestimation of activity outside the MPAs, though I would expect that most non-fishing vessel activity would not occur within the bandwidths considered for the estimates, which are very close to the protected areas. A real concern regarding these results is the lack of consideration for the implications of Protected Area Downgrading, Downsizing, and Degazettement (PADDD), which could explain higher levels of activity within MPAs (McDonald et al., 2024, Albrecht et al., 2021, Kroner et al., 2019). An additional limitation relates to compound treatment corrections (Bonilla-Mejía and Higuera-Mendieta, 2019, Keele and Titiunik, 2015), where overlap between different MPAs may introduce bias, especially in the estimates by protection level.

Finally, the findings of this article underscore the importance of utilizing increasingly reliable and accurate data to enhance the evaluation of conservation instruments, especially within the marine context. Misuse or lack of availability of data could lead to erroneous conclusions, potentially undermining the effectiveness of conservation objectives.

## References


Advani, S., Rix, L. N., Aherne, D. M., Alwany, M. A., and Bailey, D. M. (2015). Distance from a fishing community explains fish abundance in a no-take zone with weak compliance. *PLoS ONE*, 10.

Ahmadia, G. N., Glew, L., Provost, M., Gill, D., Hidayat, N. I., Mangubhai, S., Purwanto, and Fox, H. E. (2015). Integrating impact evaluation in the design and implementation of monitoring marine protected areas. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 370.

Albers, H. J., Preonas, L., Capitán, T., Robinson, E. J. Z., and Madrigal-Ballestero, R. (2020). Optimal siting, sizing, and enforcement of marine protected areas. *Environmental and Resource Economics*, 77(1):229–269.

Albrecht, R., Cook, C. N., Andrews, O., Roberts, K. E., Taylor, M. F., Mascia, M. B., and Golden Kroner, R. E. (2021). Protected area downgrading, downsizing, and degazettement (paddd) in marine protected areas. *Marine Policy*, 129:104437.

Andradi-Brown, D. A., Veverka, L., Amkieltiela, Crane, N. L., Estradivari, Fox, H. E., Gill, D., Goetze, J., Gough, C., Krueck, N. C., Lester, S. E., Mahajan, S. L., Rulmal, J., Teoh, M., and Ahmadia, G. N. (2023). Diversity in marine protected area regulations: Protection approaches for locally appropriate marine management. *Frontiers in Marine Science*, 10.

Axbard, S. (2016). Income opportunities and sea piracy in indonesia: Evidence from satellite data. *American Economic Journal: Applied Economics*, 8(2):154–94.

Bank, W. (2006). *Scaling Up Marine Management: The Role of Marine Protected Areas.* World Bank, Washington, DC. License: CC BY 3.0 IGO.

Bergseth, B. J., Russ, G. R., and Cinner, J. E. (2013). Measuring and monitoring compliance in no-take marine reserves. *Fish and Fisheries*, 16:240–258.

Bonilla-Mejía, L. and Higuera-Mendieta, I. (2019). Protected areas under weak institutions: Evidence from colombia. *World Development*, 122:585–596.

Bos, B. (2021). Fishing under the radar: Estimating compliance with fishing bans. Available at SSRN: https://ssrn.com/abstract=3871993 or http://dx.doi.org/10.2139/ssrn.3871993.

Burgess, R., Colmer, J., and Greenstone, M. (2019). The economics of marine conservation. Working Paper.

Calonico, S., Cattaneo, M. D., and Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, 82(6):2295–2326.

Campbell, S. J., Hoey, A. S., Maynard, J., Kartawijaya, T., Cinner, J., Graham, N. A., and Baird, A. H. (2012). Weak compliance undermines the success of no-take zones in a large government-controlled marine protected area. *PLoS ONE*, 7.

Canay, I. A. and Kamat, V. (2018). Approximate permutation tests and induced order statistics in the regression discontinuity design. *The Review of Economic Studies*, 85(3):1577–1608.

Cuervo-Sánchez, R., Maldonado, J. H., and Rueda, M. (2018). Spillover from marine protected areas on the pacific coast in colombia: A bioeconomic modelling approach for shrimp fisheries. *Marine Policy*, 88:182–188.

Davis, T. R. and Harasti, D. (2020). Predictive modelling of illegal fishing in no-take marine protected areas. *Fisheries Management and Ecology*, 27:292–301.

Day, J., Dudley, N., Hockings, M., Holmes, G., Laffoley, D., Stolton, S., Wells, S., and Wenzel, L. (2019). Developing capacity for a protected planet guidelines for applying the iucn protected area management categories to marine protected areas second edition. *Best Practice Protected Area Guidelines Series*.

DeVries, T., Holzer, M., and Primeau, F. (2017). Recent increase in oceanic carbon uptake driven by weaker upper-ocean overturning. *Nature*, 542(7640):215–218.

Di Cintio, A., Niccolini, F., Scipioni, S., and Bulleri, F. (2023). Avoiding "paper parks": A global literature review on socioeconomic factors underpinning the effectiveness of marine protected areas. *Sustainability*, 15(5):4464.

Diekert, F., Nøstbakken, L., and Richter, A. (2021). Control activities and compliance behavior—survey evidence from norway. *Marine Policy*, 125:104381.

Dinerstein, E., Vynne, C., Sala, E., Joshi, A. R., Fernando, S., Lovejoy, T. E., Mayorga, J., Olson, D., Asner, G. P., Baillie, J. E. M., Burgess, N. D., Burkart, K., Noss, R. F., Zhang, Y. P., Baccini, A., Birch, T., Hahn, N., Joppa, L. N., and Wikramanayake, E. (2019). A global deal for nature: Guiding principles, milestones, and targets. *Science Advances*, 5(4):eaaw2869.

Edgar, G. J., Stuart-Smith, R. D., Willis, T. J., Kininmonth, S., Baker, S. C., Banks, S., Barrett, N. S., Becerro, M. A., Bernard, A. T., Berkhout, J., Buxton, C. D., Campbell, S. J., Cooper, A. T., Davey, M., Edgar, S. C., Försterra, G., Galván, D. E., Irigoyen, A. J., Kushner, D. J., Moura, R., Parnell, P. E., Shears, N. T., Soler, G., Strain, E. M., and

Thomson, R. J. (2014). Global conservation outcomes depend on marine protected areas with five key features. *Nature*, 506:216–220.

Englander, G. (2019). Property rights and the protection of global marine resources. *Nature Sustainability*, 2.

Englander, G., Zhang, J., Villaseñor-Derbez, J. C., Jiang, Q., Hu, M., Deschenes, O., and Costello, C. (2023). Input subsidies and the destruction of natural capital: Chinese distant water fishing. Working Paper 31008, National Bureau of Economic Research.

FAO (2022). *The State of World Fisheries and Aquaculture 2022*. Food and Agriculture Organization of the United Nations.

Flückiger, M. and Ludwig, M. (2015). Economic shocks in the fisheries sector and maritime piracy. *Journal of Development Economics*, 114:107–125.

Galgano, F. A. (2024). Hostis humani generis: Pirates and global maritime commerce. *Research in Globalization*, 8:100188.

Gill, D. A., Mascia, M. B., Ahmadia, G. N., Glew, L., Lester, S. E., Barnes, M., Craigie, I., Darling, E. S., Free, C. M., Geldmann, J., Holst, S., Jensen, O. P., White, A. T., Basurto, X., Coad, L., Gates, R. D., Guannel, G., Mumby, P. J., Thomas, H., Whitmee, S., Woodley, S., and Fox, H. E. (2017). Capacity shortfalls hinder the performance of marine protected areas globally. *Nature*, 543:665–669.

Griffis, R. and Howard, J. (2013). Oceans and marine resources in a changing climate: A technical input to the 2013 national climate assessment. In Griffis, R. and Howard, J., editors, *2013 National Climate Assessment - Oceans and Marine Resources*. Island Press, Washington.

Harasti, D., Davis, T. R., Jordan, A., Erskine, L., and Moltschaniwskyj, N. (2019). Illegal recreational fishing causes a decline in a fishery targeted species (snapper: Chrysophrys auratus) within a remote no-take marine protected area. *PLoS ONE*, 14.

Herbert-Read, J. E., Thornton, A., Amon, D. J., Birchenough, S. N. R., Côté, I. M., Dias, M. P., Godley, B. J., Keith, S. A., McKinley, E., Peck, L. S., Calado, R., Defeo, O., Degraer, S., Johnston, E. L., Kaartokallio, H., Macreadie, P. I., Metaxas, A., Muthumbi, A. W. N., Obura, D. O., Paterson, D. M., Piola, A. R., Richardson, A. J., Schloss, I. R., Snelgrove, P. V. R., Stewart, B. D., Thompson, P. M., Watson, G. J., Worthington, T. A., Yasuhara, M., and Sutherland, W. J. (2022). A global horizon scan of issues impacting marine and coastal biodiversity conservation. *Nature Ecology & Evolution*, 6(9):1262–1270.

Hsu, F.-C., Elvidge, C. D., Baugh, K., Zhizhin, M., Ghosh, T., Kroodsma, D., Susanto, A., Budy, W., Riyanto, M., Nurzeha, R., and Sudarja, Y. (2019). Cross-matching viirs boat detections with vessel monitoring system tracks in indonesia. *Remote Sensing*, 11(9):995.

Jefferson, T., Palomares, M. L. D., and Lundquist, C. J. (2022). Safeguarding seafood security, marine biodiversity and threatened species: Can we have our fish and eat it too? *Frontiers in Marine Science*, 9.

Keele, L. J. and Titiunik, R. (2015). Geographic boundaries as regression discontinuities. *Political Analysis*, 23(1):127–155.

Kelaher, B. P., Page, A., Dasey, M., Maguire, D., Read, A., Jordan, A., and Coleman, M. A. (2015). Strengthened enforcement enhances marine sanctuary performance. *Global Ecology and Conservation*, 3:503–510.

Kroner, R. E. G., Qin, S., Cook, C. N., Krithivasan, R., Pack, S. M., Bonilla, O. D., Cort-Kansinally, K. A., Coutinho, B., Feng, M., Garcia, M. I. M., He, Y., Kennedy, C. J., Lebreton, C., Ledezma, J. C., Lovejoy, T. E., Luther, D. A., Parmanand, Y., Ruíz-Agudelo, C. A., Yerena, E., Zambrano, V. M., and Mascia, M. B. (2019). The uncertain future of protected lands and waters. *Science*, 364(6443):881–886.

Kroodsma, D. A., Mayorga, J., Hochberg, T., Miller, N. A., Boerder, K., Ferretti, F., Wilson, A., Bergman, B., White, T. D., Block, B. A., Woods, P., Sullivan, B., Costello, C., and Worm, B. (2018). Tracking the global footprint of fisheries. *Science*, 359(6378):904–908.

Lotze, H. K. (2021). Marine biodiversity conservation. *Current Biology*, 31(19):R1190–R1195.

Marcos, C., Díaz, D., Fietz, K., Forcada, A., Ford, A., García-Charton, J. A., Goñi, R., Lenfant, P., Mallol, S., Mouillot, D., Pérez-Marcos, M., Puebla, O., Manel, S., and Pérez-Ruzafa, A. (2021). Reviewing the ecosystem services, societal goods, and benefits of marine protected areas. *Frontiers in Marine Science*, 8.

McDonald, G., Bone, J., Costello, C., Englander, G., and Raynor, J. (2024). Global expansion of marine protected areas and the redistribution of fishing effort. *Proceedings of the National Academy of Sciences*, 121(29):e2400592121.

Miller, K. I. and Russ, G. R. (2014). Studies of no-take marine reserves: Methods for differentiating reserve and habitat effects.

NASA Goddard Space Flight Center, O. E. L. and Group, O. B. P. (2018). Moderate-resolution imaging spectroradiometer (modis) aqua ocean color data. Last accessed on August 12, 2024.

Nøstbakken, L. (2008). Fisheries law enforcement—a survey of the economic literature. *Marine Policy*, 32(3):293–300.

Ohayon, S., Granot, I., and Belmaker, J. (2021). A meta-analysis reveals edge effects within marine protected areas. *Nature Ecology and Evolution*, 5:1301–1308.

Ovando, D., Liu, O., Molina, R., Parma, A., and Szuwalski, C. (2023). Global effects of marine protected areas on food security are unknown. *Nature*, 621(7979):E34–E36.

Paolo, F. S., Kroodsma, D., Raynor, J., Hochberg, T., Davis, P., Cleary, J., Marsaglia, L., Orofino, S., Thomas, C., and Halpin, P. (2024). Satellite mapping reveals extensive industrial activity at sea. *Nature*, 625(7993):85–91.

Park, J., Lee, J., Seto, K., Hochberg, T., Wong, B. A., Miller, N. A., Takasaki, K., Kubota, H., Oozeki, Y., Doshi, S., Midzik, M., Hanich, Q., Sullivan, B., Woods, P., and Kroodsma, D. A. (2020). Illuminating dark fishing fleets in north korea. *Science Advances*, 6(30):eabb1197.

Pauly, D., Christensen, V., Guénette, S., Pitcher, T. J., Sumaila, U. R., Walters, C. J., Watson, R., and Zeller, D. (2002). Towards sustainability in world fisheries. *Nature*, 418(6898):689–695.

Pauly, D. and Zeller, D. (2016). Catch reconstructions reveal that global marine fisheries catches are higher than reported and declining. *Nature Communications*, 7(1):10244.

Rife, A. N., Erisman, B., Sanchez, A., and Aburto-Oropeza, O. (2013). When good intentions are not enough... insights on networks of "paper park" marine protected areas. *Conservation Letters*, 6(3):200–212.

Rising, J. and Heal, G. (2014). Global benefits of marine protected areas. Working Paper 19982, National Bureau of Economic Research.

Roberts, C. M., Bohnsack, J. A., Gell, F., Hawkins, J. P., and Goodridge, R. (2001). Effects of marine reserves on adjacent fisheries. *Science*, 294(5548):1920–1923.

Rodríguez-Rodríguez, D., Rees, S., Rodwell, L., and Attrill, M. (2015). Assessing the socioeconomic effects of multiple-use mpas in a european setting: A national stakeholders' perspective. *Environmental Science  Policy*, 48:115–127.

Russ, G. R., Alcala, A. C., and Maypa, A. P. (2003). Spillover from marine reserves: the case of naso vlamingii at apo island, the philippines. *Marine Ecology Progress Series*, 264:15–20.

Sala, E. and Giakoumi, S. (2018). No-take marine reserves are the most effective protected areas in the ocean. *ICES Journal of Marine Science*, 75:1166–1168.

Semedi, B. and Hadiyanto, A. L. (2013). Forecasting the fishing ground of small pelagic fishes in makassar strait using moderate resolution image spectroradiometer satellite images. *Journal of Applied Environmental and Biological Sciences*, 3(2):29–34.

Smith, M. K. S., Smit, I. P., Swemmer, L. K., Mokhatla, M. M., Freitag, S., Roux, D. J., and Dziba, L. (2021). Sustainability of protected areas: Vulnerabilities and opportunities as revealed by covid-19 in a national park management agency. *Biological Conservation*, 255:108985.

UNEP-WCMC and IUCN (2021). Protected planet report 2020.

Wang, K., Reimer, M. N., and Wilen, J. E. (2023). Fisheries subsidies reform in china. *Proceedings of the National Academy of Sciences*, 120(26):e2300688120.

Ward, D., Melbourne-Thomas, J., Pecl, G. T., Evans, K., Green, M., McCormack, P. C., Novaglio, C., Trebilco, R., Bax, N., Brasier, M. J., Cavan, E. L., Edgar, G., Hunt, H. L., Jansen, J., Jones, R., Lea, M.-A., Makomere, R., Mull, C., Semmens, J. M., Shaw, J., Tinch, D., van Steveninck, T. J., and Layton, C. (2022). Safeguarding marine life: conservation of biodiversity and ecosystems. *Reviews in Fish Biology and Fisheries*, 32(1):65–100.

Watson, A. J., Schuster, U., Shutler, J. D., Holding, T., Ashton, I. G. C., Landschützer, P., Woolf, D. K., and Goddijn-Murphy, L. (2020). Revised estimates of ocean-atmosphere co2 flux are consistent with ocean carbon inventory. *Nature Communications*, 11(1):4422.

Watson, R. and Pauly, D. (2001). Systematic distortions in world fisheries catch trends. *Nature*, 414:534–536.

Welch, H., Clavelle, T., White, T. D., Cimino, M. A., Osdel, J. V., Hochberg, T., Kroodsma, D., and Hazen, E. L. (2022). Hot spots of unseen fishing vessels. *Science Advances*, 8(44):eabq2109.

Ziegler, S. L., Brooks, R. O., Hamilton, S. L., Ruttenberg, B. I., Chiu, J. A., Fields, R. T., Waltz, G. T., Shen, C., Wendt, D. E., and Starr, R. M. (2022). External fishing effort regulates positive effects of no-take marine protected areas. *Biological Conservation*, 269:109546.

# Appendix. Additional Tables and Figures

*Table A1. Descriptive statistics by levels of protection*

| | Levels of protection | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| *Outcome variables* | | | | | |
| Fishing Hours per 1000 $km^2$ | 904.4 | 387.4 | 138.4 | 46.32 | 145.5 |
| Vessels detection using AIS per 1000 $km^2$ | 147.8 | 151.9 | 56.94 | 23.59 | 42.60 |
| Vessels detection using SAR per 1000 $km^2$ | 153.1 | 76.90 | 104.4 | 68.72 | 108.6 |
| Unseen vessel detection using SAR per 1000 $km^2$ | 29.08 | 20.13 | 50.49 | 15.31 | 61.39 |
| Pr(Unseen vessel detection using SAR) | 0.65 | 0.56 | 0.55 | 0.49 | 0.67 |
| | | | | | |
| *Environmental conditions* | | | | | |
| Sea surface temperature (°C) | 19.33 | 11.26 | 10.38 | 20.59 | 21.78 |
| Chlorophyll concentration | 1.33 | 1.20 | 0.55 | 0.21 | 0.30 |
| Phytoplankton absorption | 1.27 | 1.71 | 1.14 | 0.45 | 0.62 |
| | | | | | |
| *Grid characteristics* | | | | | |
| Distance to MPAs boundary (km) | 24 | 89 | 103 | 62 | 68 |
| Distance to Ports (m) | 527 | 333 | 1,986 | 919 | 784 |
| Distance to Shore (m) | 111.9 | 165.8 | 183.3 | 190.8 | 195.8 |
| Distance to Seamounts (m) | 188,656 | 320,675 | 158.912 | 137,612 | 139,031 |
| Distance to Pïracy events (m) | 817,149 | 2,290,859 | 2,491,678 | 2,007,648 | 1,886,791 |
| Depth (m) | -1,616 | -1,656 | -1,205 | -2,227 | -1,861 |

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: The table presents the means for observations within each marine protected area according to its level of protection for the period 2017–2019.

*Table A2. AIS Fishing efforts and SAR vessel detections*

| | *Fishing efforts (ln)* | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Vessel detections SAR (ln) | 0.79*** | 0.79*** | 0.61*** | 0.13*** | 0.13*** |
| | (0.002) | (0.002) | (0.006) | (0.004) | (0.017) |
| | | | | | |
| Observations | 490,095 | 490,095 | 103,077 | 405,913 | 27,819 |
| Year FE | No | Yes | No | Yes | Yes |
| Grid FE | No | No | No | Yes | Yes |
| Climate Variables | No | No | Yes | No | Yes |
| Grid characteristics | No | No | Yes | No | No |

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. Robust standards errors in parentheses.

*Table A3. Determinants of industrial activity inside of MPAs*

| | *Fishing Hours per 1000 $km^2$* | *Vessels detection per 1000 $km^2$* | | *Unseen vessel detection using SAR per 1000 $km^2$* | *Pr(Unseen vessel detection using SAR)* |
|---|---|---|---|---|---|
| | | *AIS* | *SAR* | | |
| | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* |
| *Panel A. Environmental variables* | | | | | |
| Sea surface temperature | -208.3*** | -10.39*** | -3.69 | -3.20* | -0.22 |
| | (72.03) | (2.50) | (3.55) | (1.89) | (0.014) |
| Phytoplankton absorption | -44.27** | 1.19 | 0.23 | 3.39** | 0.022** |
| | (17.07) | (1.37) | (2.81) | (1.51) | (0.011) |
| Chlorophyll-a concentration | 42.99 | 0.81 | -3.63 | 0.97 | 0.013 |
| | (26.884) | (2.05) | (3.28) | (1.01) | (0.012) |
| 1.Fishing Condition | 53.13 | 18.75 | -2.52 | 1.34 | -0.023 |
| | (189.6) | (20.62) | (5.74) | (5.19) | (0.16) |
| Observations | 8,727 | 8,727 | 2,760 | 2,760 | 2,760 |
| *Panel B. Biological and characteristics variables* | | | | | |
| Distance to piracy events | 0.011** | 0.0002 | 0.00003 | 0.00006** | -2.09e-07 |
| | (0.006) | (0.0002) | (0.0005) | (0.0003) | (1.87e-07) |
| Distance to Shore | -4.77 | -0.66* | -0.074 | -0.16*** | -0.002*** |
| | (8.81) | (0.36) | (0.05) | (0.028) | (0.0004) |
| Distance to Ports | -3.67 | -0.50 | -0.43*** | 0.011 | 0.0008*** |
| | (8.21) | (0.31) | (0.07) | (0.029) | (0.0002) |
| Distance to seamounts | 0.01* | 0.0001 | -0.00007** | 0.00006*** | 4.38e-07*** |
| | (0.004) | (0.0001) | (0.00004) | (0.00001) | (1.60e-07) |
| Depth | 8.38*** | 0.22 | 0.026*** | -0.005 | 0.00003 |
| | (2.88) | (0.16) | (0.01) | (0.004) | (0.00005) |
| Observations | 196 | 196 | 253 | 253 | 253 |

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. All estimations were performed with year and grid fixed effects. Robust standard errors are in parentheses. In Panel B, year and grid fixed effects are not included since these are invariant characteristics, and the sample is restricted to periods that coincide with piracy events.

*Table A4. Regression discontinuity effect of MPAs on Fishing activity using SAR data by level of protection*

| | *Vessels detection using SAR per 1000 km$^2$* | | | *Unseen vessel detection using SAR per 1000 km$^2$* | | | *Pr(Unseen vessel detection using SAR)* | | |
|---|---|---|---|---|---|---|---|---|---|
| | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* | *Optimal Bandwidth* | *Fixed Bandwidth* | *Donut hole* |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Level of protection = 1* | | | | | | | | | |
| Conventional | -34.78 | -111.1*** | -118.6*** | -15.51*** | -25.61*** | -42.38*** | 0.017 | -0.019 | 0.086 |
| | (39.33) | (17.03) | (37.05) | (5.77) | (3.30) | (6.93) | (0.026) | (0.015) | (0.053) |
| Bias-corrected | -20.23 | -116.6*** | -130.5*** | -12.85** | -23.94*** | -42.8*** | 0.022 | -0.029* | 0.10* |
| | (39.33) | (17.03) | (37.05) | (5.77) | (3.30) | (6.93) | (0.026) | (0.015) | (0.053) |
| Robust | -20.23 | -116.6*** | -130.5*** | -12.85** | -23.94*** | -42.8*** | 0.022 | -0.029 | 0.10 |
| | (43.34) | (23.95) | (44.17) | (6.52) | (4.61) | (8.41) | (0.031) | (0.020) | (0.062) |
| bandwidth (km) | 7.54 | 50 | 16.17 | 13.03 | 50 | 11.62 | 14.35 | 50 | 9.86 |
| Observations | 20,204 | 64,079 | 18,908 | 20,204 | 64,079 | 18,908 | 20,204 | 64,079 | 18,908 |
| *Level of protection = 2* | | | | | | | | | |
| Conventional | -107.0*** | -122.6*** | -189.4*** | -3.39 | -5.11** | -1.52 | 0.018 | 0.026** | 0.11** |
| | (21.49) | (13.89) | (45.86) | (3.21) | (2.08) | (5.90) | (0.020) | (0.013) | (0.044) |
| Bias-corrected | -103.4*** | -112.3*** | -205.7*** | -3.00 | 0.24 | -0.97 | 0.019 | 0.025* | 0.118*** |
| | (21.49) | (13.89) | (45.86) | (3.21) | (2.08) | (5.90) | (0.020) | (0.013) | (0.044) |
| Robust | -103.4*** | -112.3*** | -205.7*** | -3.00 | 0.24 | -0.97 | 0.019 | 0.025 | 0.118** |
| | (24.98) | (19.04) | (54.35) | (3.74) | (2.82) | (7.08) | (0.023) | (0.018) | (0.054) |
| bandwidth (km) | 17.18 | 50 | 10 | 11.41 | 50 | 11.13 | 16.4 | 50 | 9.05 |
| Observations | 17,432 | 47,816 | 16,051 | 17,432 | 47,816 | 16,051 | 17,432 | 47,816 | 16,051 |
| *Level of protection = 3* | | | | | | | | | |
| Conventional | 35.82 | -33.68 | 735.3 | -19.31* | -14.97** | -8.31 | -0.13*** | -0.070** | 0.022 |
| | (42.43) | (39.72) | (495.9) | (10.83) | (5.78) | (14.92) | (0.049) | (0.029) | (0.106) |
| Bias-corrected | 48.51 | -25.13 | 931.2* | -22.83** | -16.51*** | -9.40 | -0.145*** | -0.099*** | 0.027 |
| | (42.43) | (39.72) | (495.9) | (10.83) | (5.78) | (14.92) | (0.049) | (0.029) | (0.106) |
| Robust | 48.51 | -25.13 | 931.2 | -22.83* | -16.51* | -9.40 | -0.145** | -0.099** | 0.027 |
| | (42.13) | (48.23) | (602.6) | (13.66) | (9.34) | (19.23) | (0.058) | (0.039) | (0.131) |
| bandwidth (km) | 10.93 | 50 | 6.17 | 19.74 | 50 | 18.58 | 11.51 | 50 | 8.66 |
| Observations | 4,758 | 16,970 | 4,469 | 4,758 | 16,970 | 4,469 | 4,758 | 16,970 | 4,469 |
| *Level of protection = 4* | | | | | | | | | |
| Conventional | -220.4*** | -181.8*** | -86.16 | -11.03* | -6.25 | -19.92** | -0.01 | -0.002 | -0.133 |
| | (64.34) | (36.91) | (99.71) | (6.55) | (4.28) | (10.11) | (0.088) | (0.058) | (0.160) |
| Bias-corrected | -212.8*** | -214.8*** | -52.98 | -9.97 | -10.93** | -23.1** | 0.012 | -0.045 | -0.129 |
| | (64.34) | (36.91) | (99.71) | (6.55) | (4.28) | (10.11) | (0.088) | (0.058) | (0.160) |
| Robust | -212.8*** | -214.8*** | -52.98 | -9.97 | -10.93* | -23.1* | 0.012 | -0.045 | -0.129 |
| | (73.76) | (53.75) | (121.3) | (7.61) | (5.71) | (12.11) | (0.100) | (0.078) | (0.197) |
| bandwidth (km) | 13.08 | 50 | 12.84 | 13.91 | 50 | 8.67 | 16.14 | 50 | 12.08 |
| Observations | 2,103 | 7,756 | 2,006 | 2,103 | 7,756 | 2,006 | 2,103 | 7,756 | 2,006 |
| *Level of protection = 5* | | | | | | | | | |
| Conventional | -65.35 | -129.2*** | -276.5** | -2.91 | -1.60 | 46.38 | -0.168* | -0.066 | 1.943*** |
| | (56.09) | (28.57) | (132.2) | (23.45) | (14.52) | (53.36) | (0.094) | (0.049) | (0.618) |
| Bias-corrected | -47.11 | -136.3*** | -286.3** | -7.31 | 6.72 | 48.65 | -0.206** | -0.093* | 2.267*** |
| | (56.09) | (28.57) | (132.2) | (23.45) | (14.52) | (53.36) | (0.094) | (0.049) | (0.618) |
| Robust | -47.11 | -136.3*** | -286.3* | -7.31 | 6.72 | 48.65 | -0.206* | -0.093 | 2.267*** |
| | (64.47) | (41.49) | (163.2) | (27.11) | (19.61) | (63.95) | (0.106) | (0.063) | (0.657) |
| bandwidth (km) | 7.77 | 50 | 6.27 | 11.48 | 50 | 14.63 | 5.41 | 50 | 3.52 |
| Observations | 5,032 | 23,556 | 4,863 | 5,032 | 23,556 | 4,863 | 5,032 | 23,556 | 4,863 |

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. Calonico et al. (2014) RD estimate used with optimal bandwidth (columns 1, 4 and 7), fixed 50 kms bandwidth (columns 2, 5 and 8), and 2km donut hole approach (columns 3, 6 and 9). All regressions control for the climatic, physical and biological variables. I present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

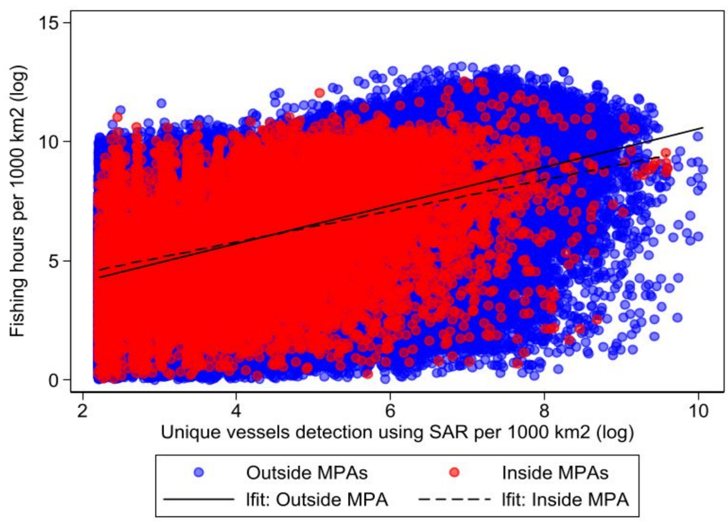
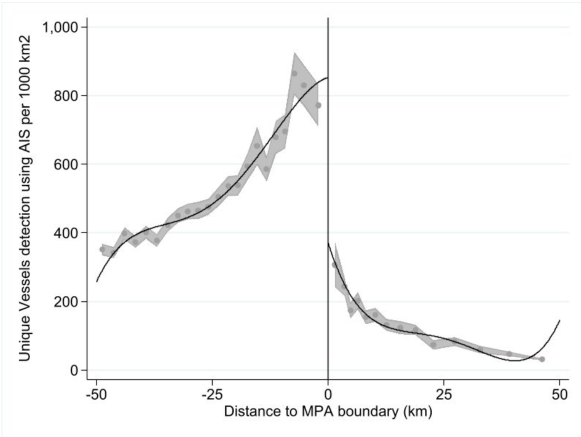
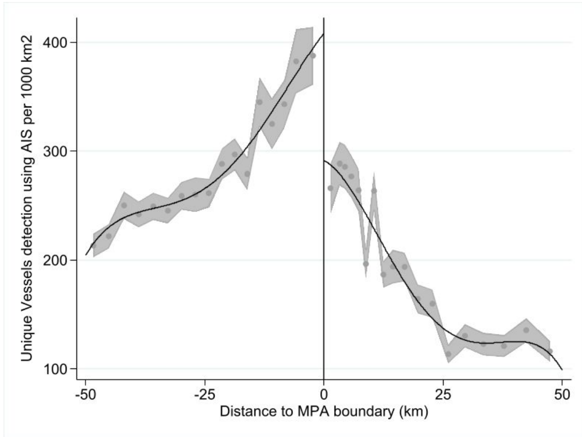


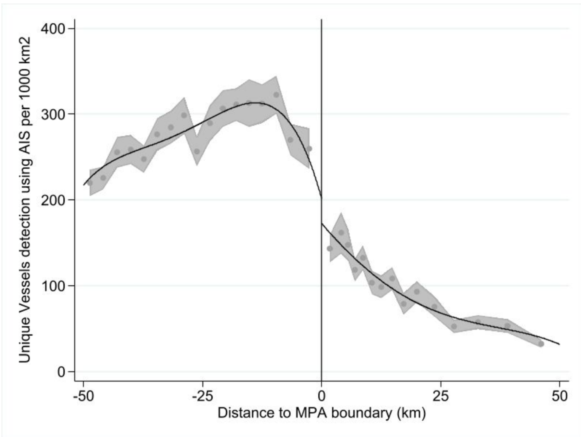

Figure A1. Correlation of AIS Fishing Hours and SAR Vessel Detections



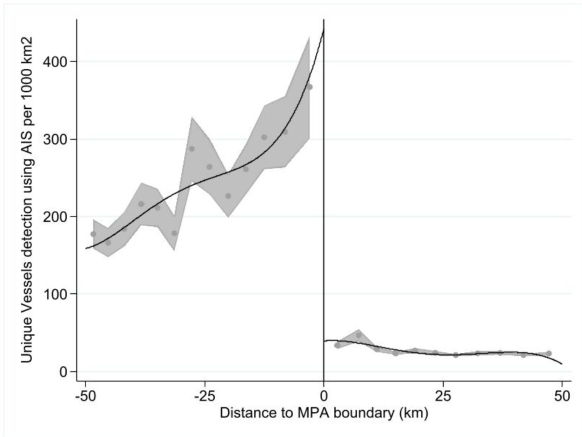

*(a) Level 1*



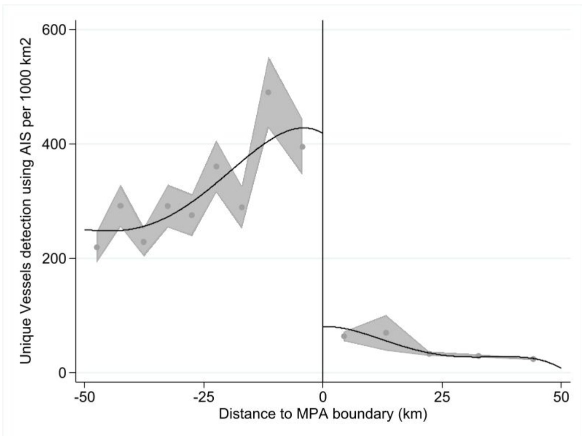

*(b) Level 2*




*(c) Level 3*

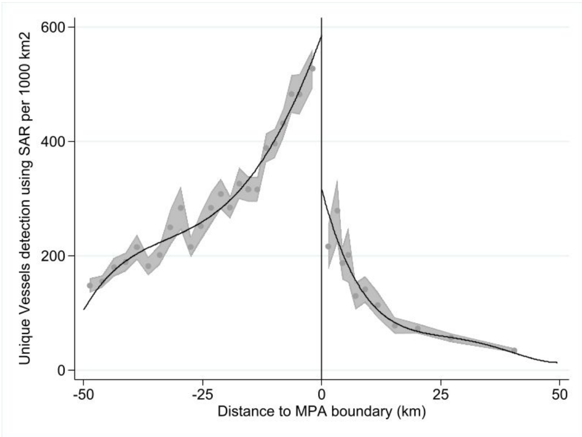



*(d) Level 4*

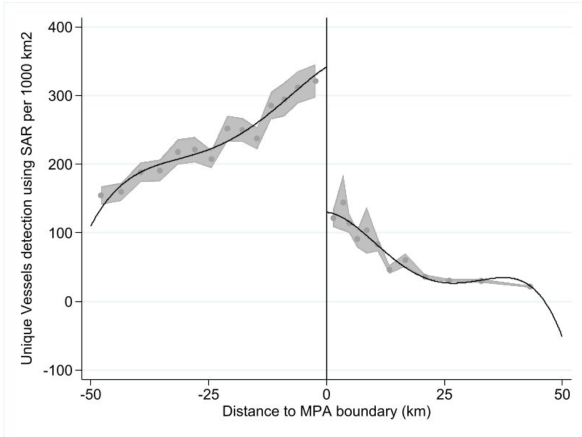



*(e) Level 5*

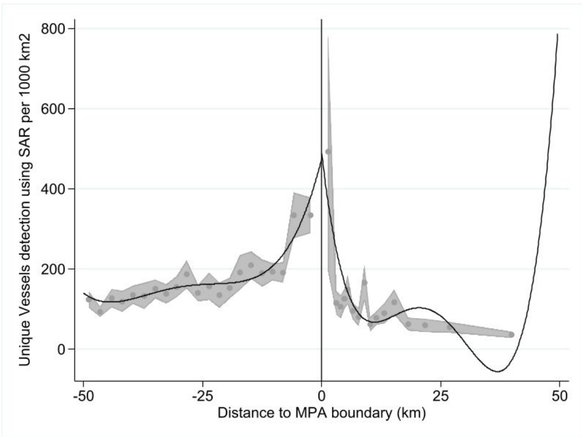
Figure A2. Regression discontinuity effect of MPAs on vessel detections using AIS data by levels of protection.
Note: All graphs present the estimates following the donut hole approach with a 2km exclusion zone.



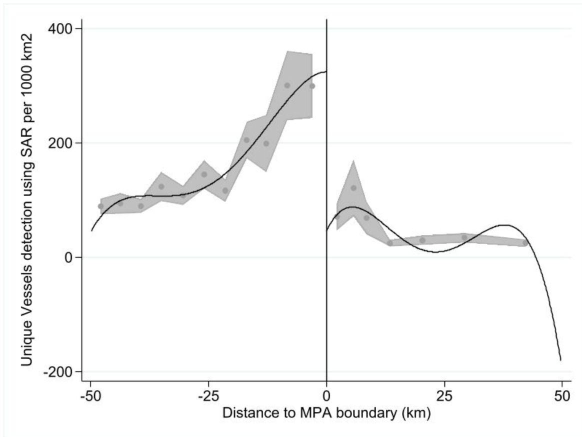

***(a)** Level 1*



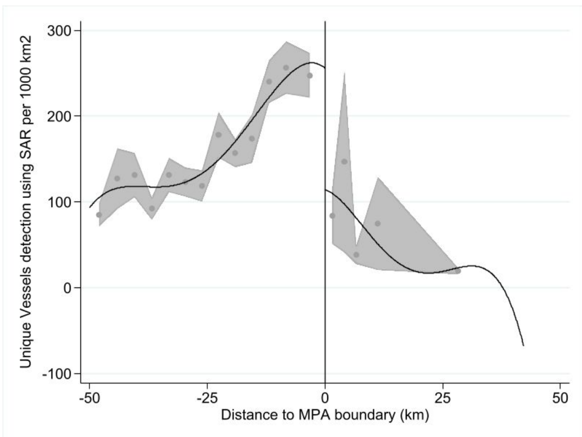

***(b)** Level 2*




***(c)** Level 3*

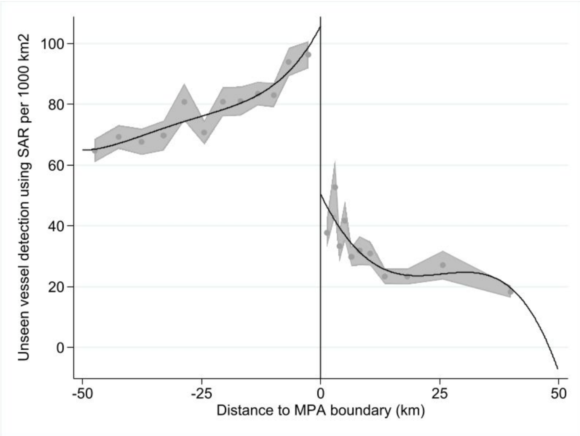



***(d)** Level 4*

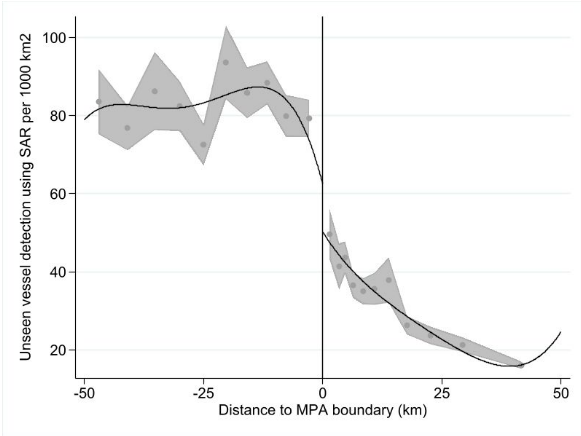



***(e)** Level 5*

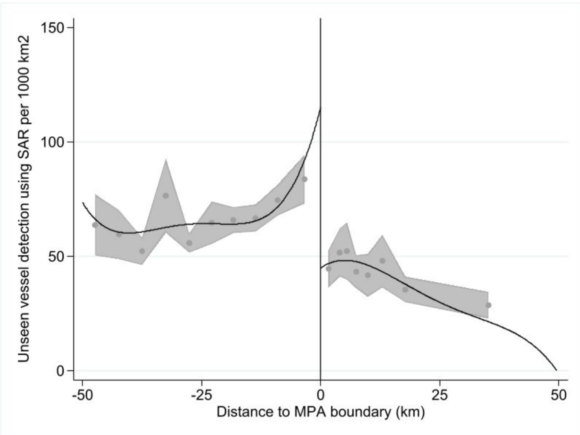
Figure A3. Regression discontinuity effect of MPAs on vessel detections using SAR data by levels of protection.
Note: All graphs present the estimates following the donut hole approach with a 2km exclusion zone.



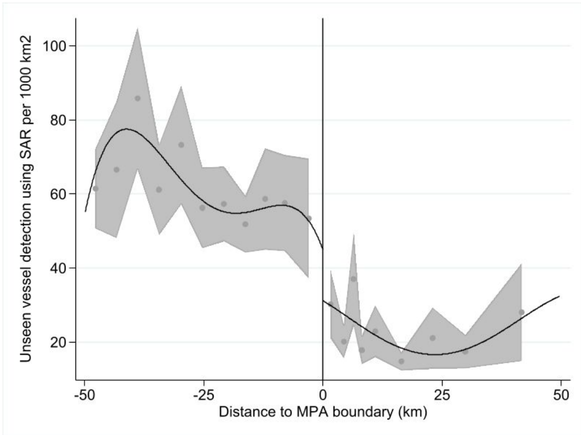

*(a) Level 1*



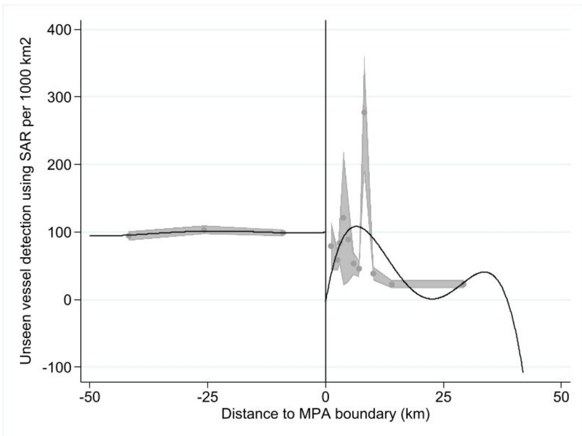

*(b) Level 2*




*(c) Level 3*

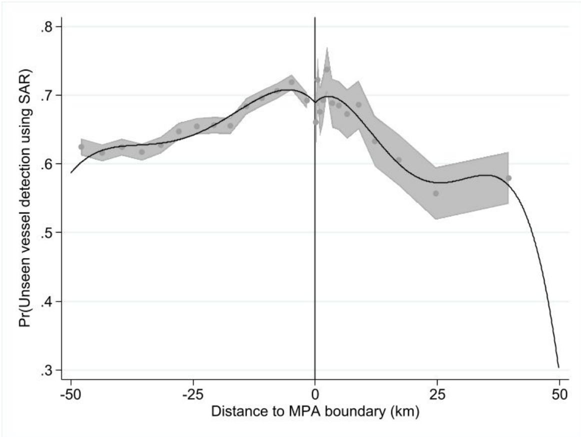



*(d) Level 4*

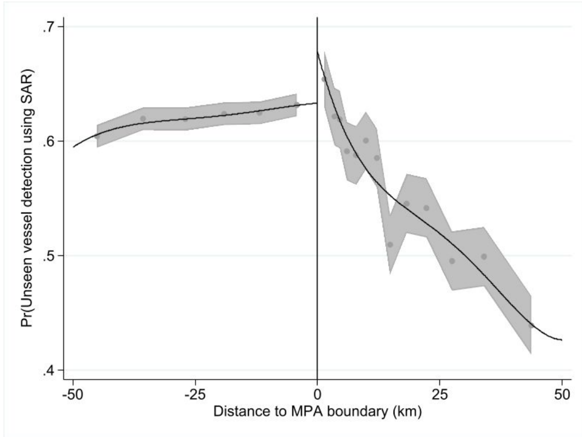



*(e) Level 5*

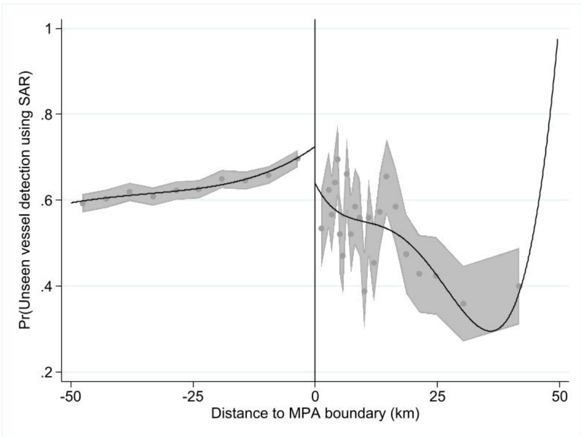
Figure A4. Regression discontinuity effect of MPAs on vessel detctions no-publicly tracked by levels of protection. Note: All graphs present the estimates following the donut hole approach with a 2km exclusion zone.



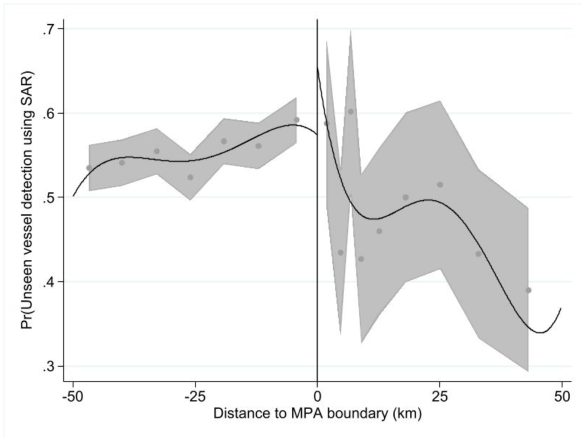

***(a)*** *Level 1*



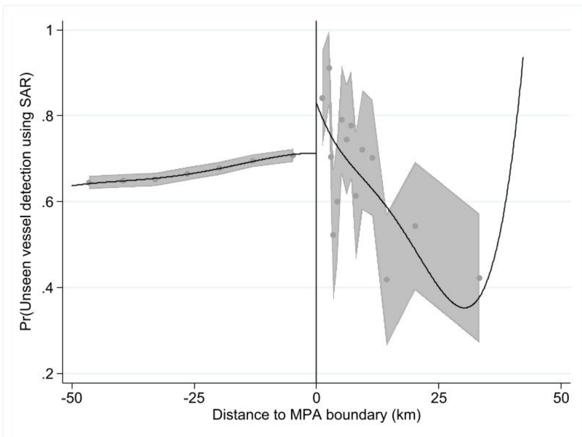

***(b)*** *Level 2*




***(c)*** *Level 3*

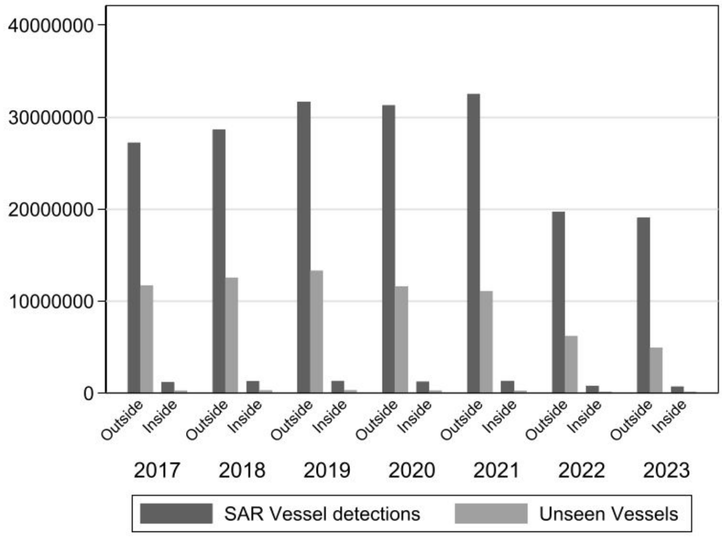



***(d)*** *Level 4*

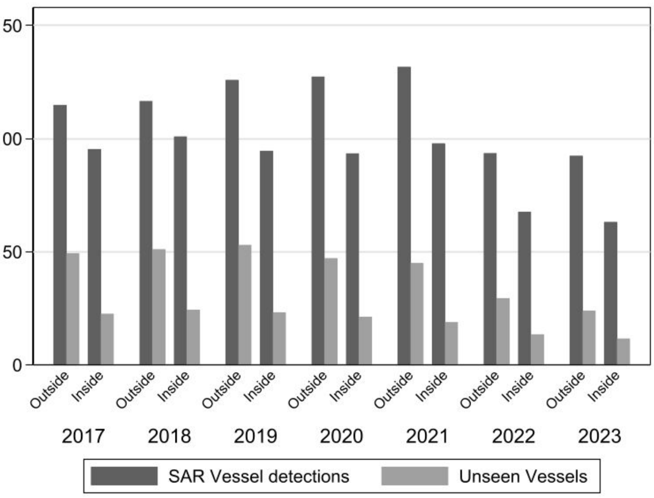



***(e)*** *Level 5*

Figure A5. Regression discontinuity effect of MPAs on probability of vessel detctions no-publicly tracked by levels of protection. Note: All graphs present the estimates following the donut hole approach with a 2km exclusion zone.

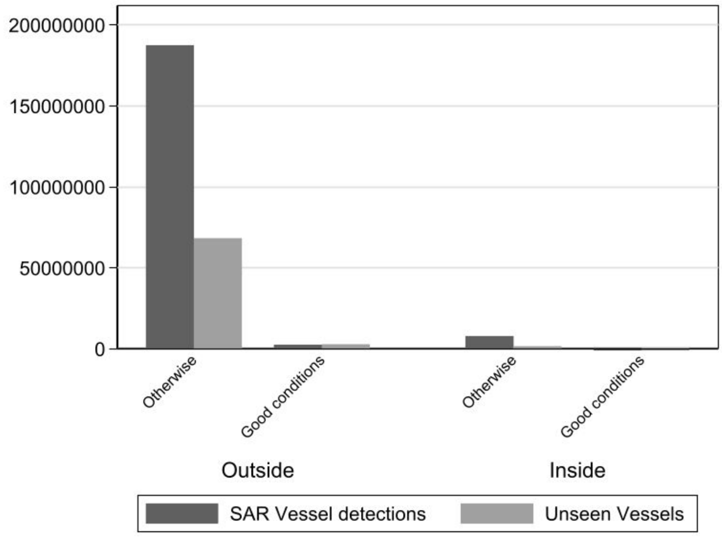



***(a)*** *SAR fishing Activity: Sum*

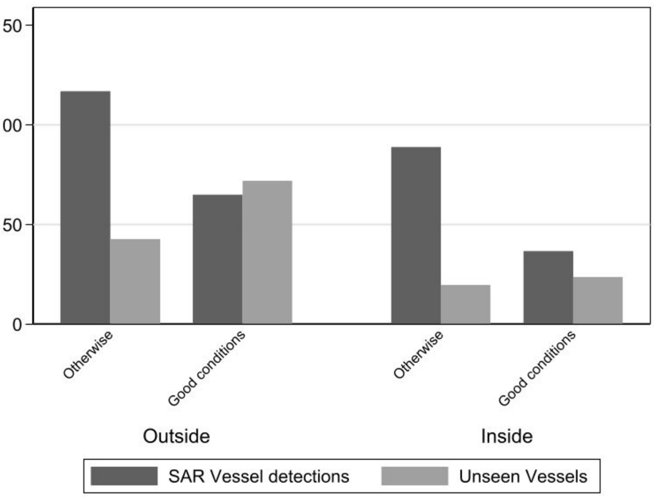



***(b)*** *SAR fishing Activity: Mean*

Figure A6. SAR Fishing Activity by years. Note: Panel A shows the total fishing activity using SAR data for the years in the sample. Panel B shows the annual average.

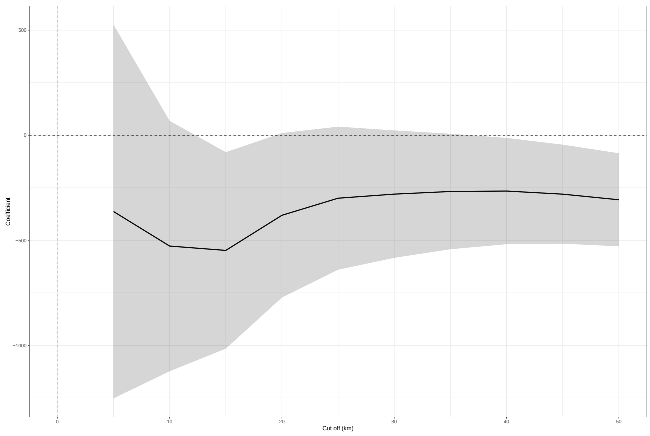



***(a)*** *SAR fishing Activity: Sum*

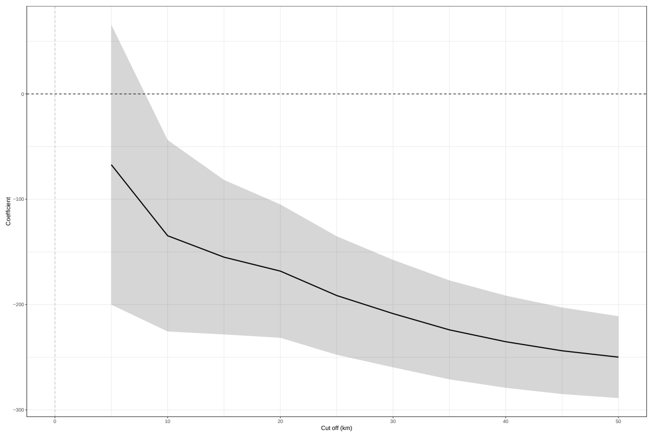



***(b)*** *SAR fishing Activity: Mean*

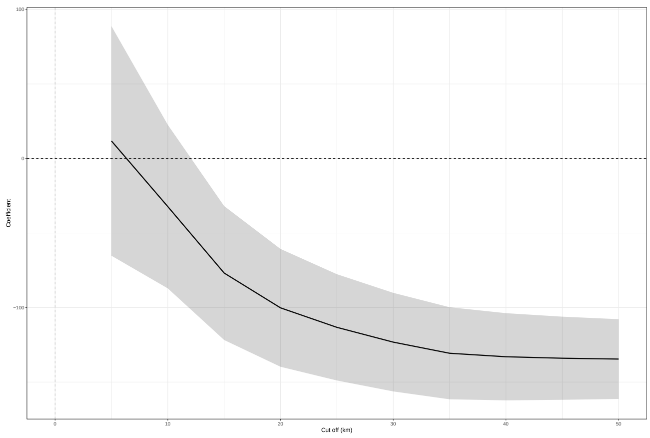
Figure A7. SAR Fishing Activity by fishing conditions. Note: Panel A shows the total fishing activity using SAR data by fishing condition. Panel B shows the average by fishing conditions.




***(a)*** *Fishing hours*

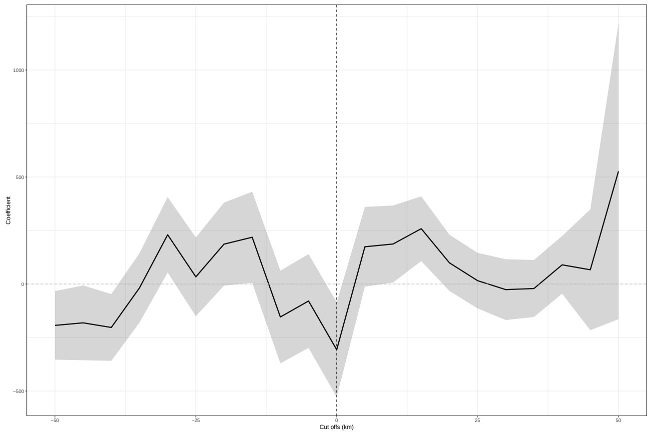



***(b)*** *Vessels detected using AIS*

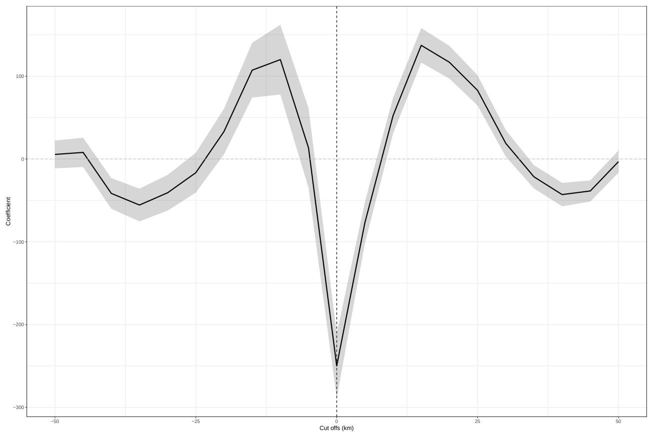



***(c)*** *Vessels detected using SAR*

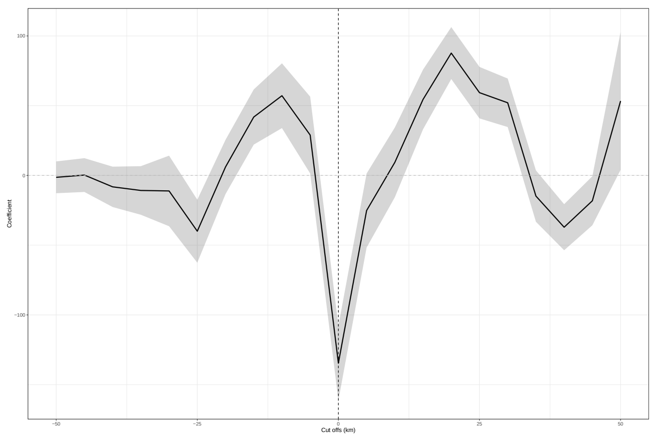
Figure A8. Bandwidth Sensitivity




***(a)*** *Fishing hours*




***(b)*** *Vessels detected using AIS*




***(c)*** *Vessels detected using SAR*

Figure A9. Placebo threshold test for RD effects