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, we examine the dynamics and behavior of industrial fishing vessels in relation to MPAs, leveraging extensive global fishing data. Using a regression discontinuity design, we evaluate vessel compliance by analyzing their presence within MPAs through 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 regions such as Indonesia, the Horn of Africa, and the Central Caribbean, regions characterized as a hotspot for piracy events, good fishing conditions, and consequently, non-publicly tracked vessels. We also find that fishing efforts decrease within less productive MPAs, while no significant effects are observed in the more productive ones. Additionally, larger MPAs and those located farther from piracy-prone regions are more effective in controlling fishing activity.

Key words: Marine Protected Areas, Industrial Fishing, Compliance, Satellite Monitoring.
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), highlighting the importance of using more transparent data for accurately assessing ecosystem sustainability.

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, Kroner et al., 2019). 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 a significant sample of existing MPAs are fulfilling the conservation goals for which they were established.

In this paper, we 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, we employ causal inference techniques and econometric methods that allow us to capture the causal effect of MPAs on industrial activity at a global scale. We 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, we also explore the heterogeneities driven by varying levels of fishing restrictions. Furthermore, to deepen our understanding of fishermen's motivations, we assess the relationship between industrial fishing activity within MPAs and observable characteristics such as MPA size, distance to the shore, ports, and piracy events; and fishing conditions.

Based on the results, we 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 Neal (2024), Englander (2019) and Bonilla-Mejía and Higuera-Mendieta (2019).

We also find that there is no evidence suggesting that higher protection levels lead to better outcomes in terms of reducing the number of both publicly and non-publicly tracked vessels. This unexpected result is reasonable given that MPAs with stricter fishing restrictions do not significantly reduce the number of vessels entering but do decrease the total fishing hours conducted within their boundaries. This suggests that vessels may still enter, but the greater enforcement effectiveness reduces the amount of time they spend fishing inside. These results are also in line with theoretical predictions.

As suggested in the literature, enforcement is typically more effective closer to shore and ports (Albers et al., 2020). In this regard, we find that MPAs closer to the shore are indeed more effective in reducing fishing activity within their boundaries compared to those farther away, particularly in terms of the number of vessels. These results remain consistent when using SAR data. Additionally, MPAs located closer to ports show a greater reduction in fishing activity, both when detected through SAR and AIS data. Notably, these reductions are even larger than those related to shore distance. In terms of MPA size, we observe that larger MPAs are effective in reducing fishing activity within their boundaries, both in terms of total fishing efforts and the number of vessels entering. This result suggests that, despite the greater difficulty in monitoring and enforcement associated with larger MPAs, the managing institutions have been effective in overseeing these larger areas.

Furthermore, considering that fishers operate where fish stocks are more abundant, we find that fishing efforts decrease within MPAs with poor fishing conditions or those that had favorable conditions for only one year—in other words, the less productive MPAs. In contrast, no significant effects are observed in MPAs with favorable fishing conditions for at least two of the three years (2017–2019), meaning the more productive MPAs. Finally, we find no significant effects in MPAs near regions with high piracy prevalence, except for the number of vessels detected using SAR data. In contrast, for MPAs farther from piracy-prone regions, their effectiveness in controlling fishing activity is evident.

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 exploring the relationship between observable factors such as MPA size; distance to the shore, ports, and piracy events, as well as fishing conditions, and their influence on compliance levels within MPAs at global level.

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, we include data from satellite imagery in addition to AIS information, which can be manipulated by fishers (Welch et al., 2022). Second, we use a distinct database of protected areas, allowing for evidence focused on different levels of fishing protection. Third, we aim to explore potential factors explaining changes in fisher compliance.

The findings of this article suggest that MPAs are an effective tool in the fight against overfishing. Proper management and the appropriate use of monitoring and control tools play a crucial role in the effectiveness of MPAs. Although conservation restricts fishing activity in the short term, greater conservation creates medium-term incentives that help preserve and increase the availability of fish stocks for fishing. Additionally, the results of this article underscore the importance of using increasingly reliable and accurate data to improve the evaluation of conservation instruments, particularly in the marine context. Misuse or lack of data availability could lead to erroneous conclusions, potentially undermining conservation efforts. Furthermore, the study highlights the importance of effective enforcement in ensuring 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. The findings on the relationship between law enforcement and MPA effectiveness are discussed, along with an assessment of key determinants such as piracy and biological fishing conditions. Finally, section 5 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, we compiled a global database of ocean activity using AIS and satellite data at a 0.1-degree resolution for coastal waters from 2017 to 2019. The dataset also includes climatic, biological, and biophysical information for each coastal grid[2].

2.1 AIS Fishing Activity Data

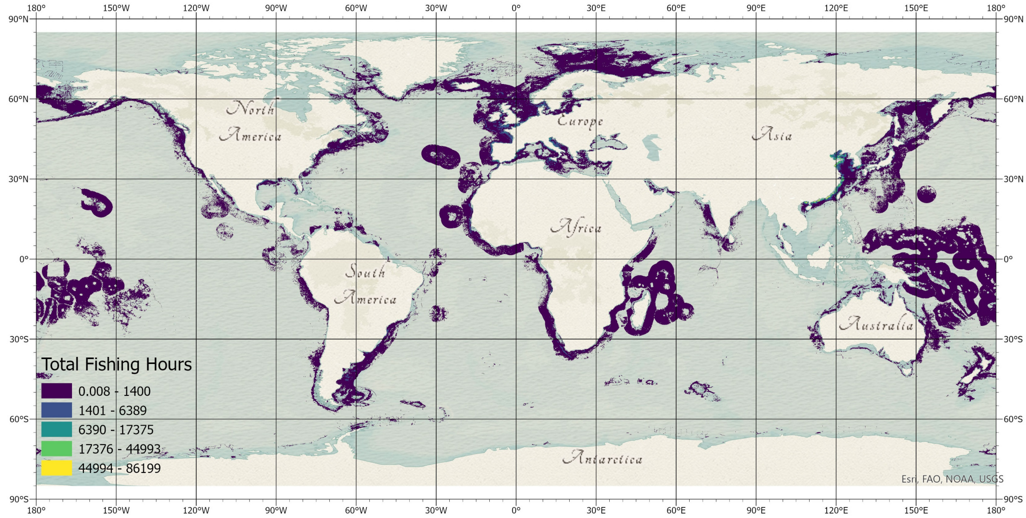
The Automatic Identification System (AIS) was originally designed to prevent vessel collisions by transmitting location, identity, speed, and heading to nearby ships. However, the use of AIS data has become increasingly important for monitoring fishing activity due to its ease of collection, accessibility, 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 Horn of Africa, 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.

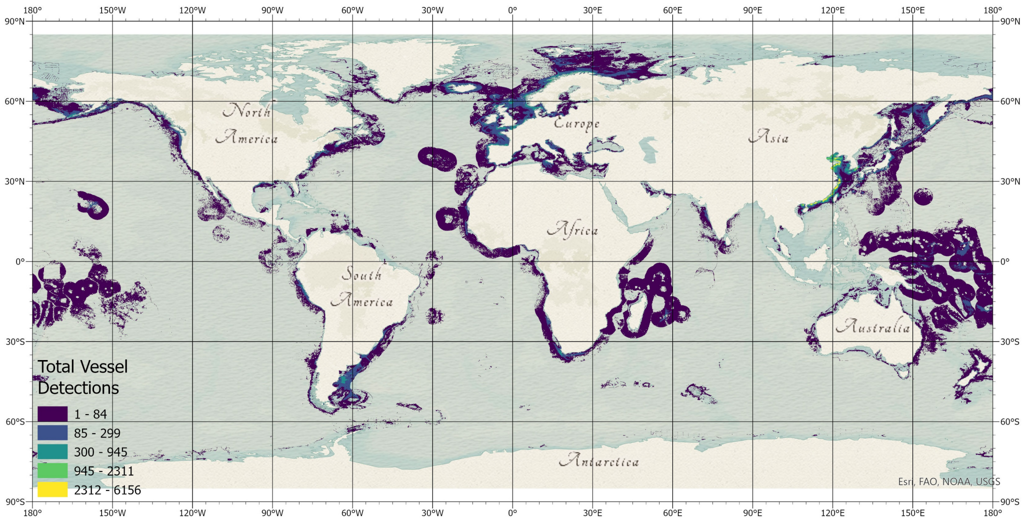
2.2 SAR Fishing Activity Data

We 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).

[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: Panel A presents the cumulative fishing hours between 2017 and 2019. Panel B shows the number of vessels detected via AIS between 2017 and 2019. Observations are aggregated to a 1km resolution grid for each EEZ.

This information allows us 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 us 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.

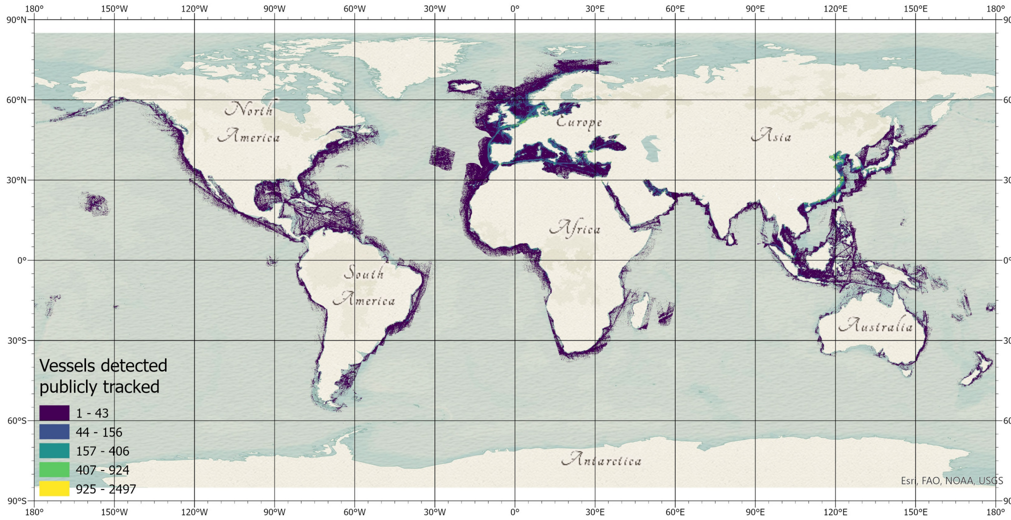
Figure 2 illustrates the extent of industrial activity detected in global coastal areas during the 2017–2019 period. Panel A shows the tracked activity linked to Maritime Mobile Service Identities (MMSI), which are identifiers associated with AIS transmitters. In contrast, Panel B depicts vessels detected 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) or "non-publicly tracked vessels" (Paolo et al., 2024). 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 Horn of Africa, and the Central Caribbean.

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 our 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.

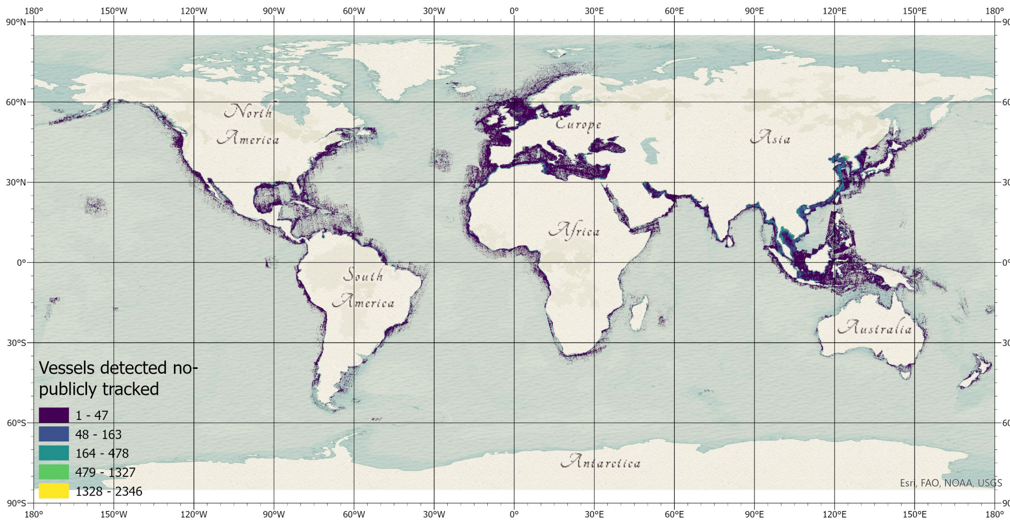
2.3 Comparing AIS Fishing Efforts and SAR vessels detections

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 A3), estimate that aligns with that obtained by Bos (2021) using VIIRS data in China.



(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: Panel A presents the number of vessels detected via SAR that could be tracked alongside AIS data between 2017 and 2019. Panel B shows the number of vessels detected via SAR that could not be tracked alongside AIS data between 2017 and 2019. Observations are aggregated to a 1km resolution grid for each EEZ.

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 us to obtain a comparable measure of the protection level of each MPA. We 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 the map of the MPAs considered in the study (Panel A) and the coverage of protected areas within each EEZs (Panel B).

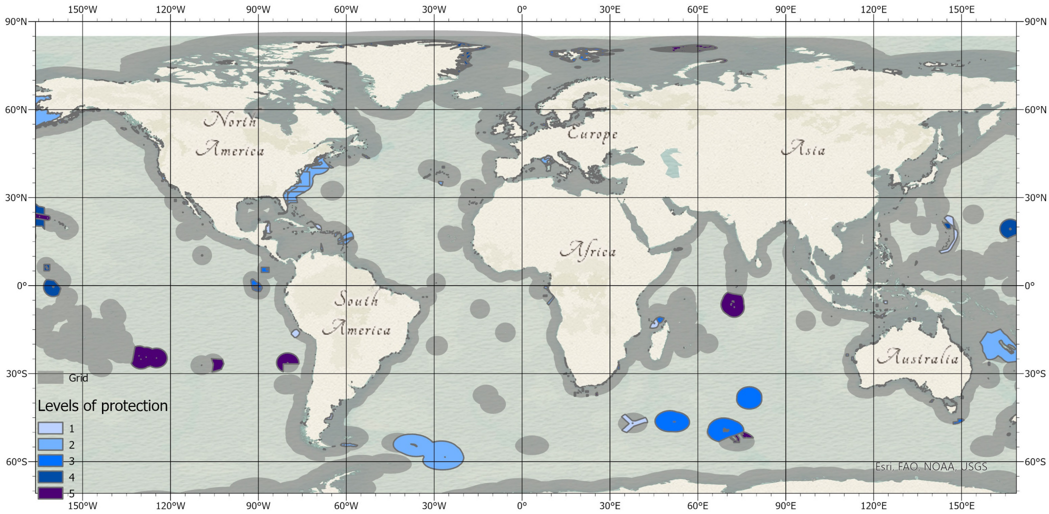
The significance of the ProtectedSeas database lies in its proposal of a specialized coding system for categorizing the restrictions related to fishing activity. This measure includes five categories: Least restrictive (=1), no known fishing restrictions; Less restrictive (=2), few species- or gear-specific 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 Biological Variables

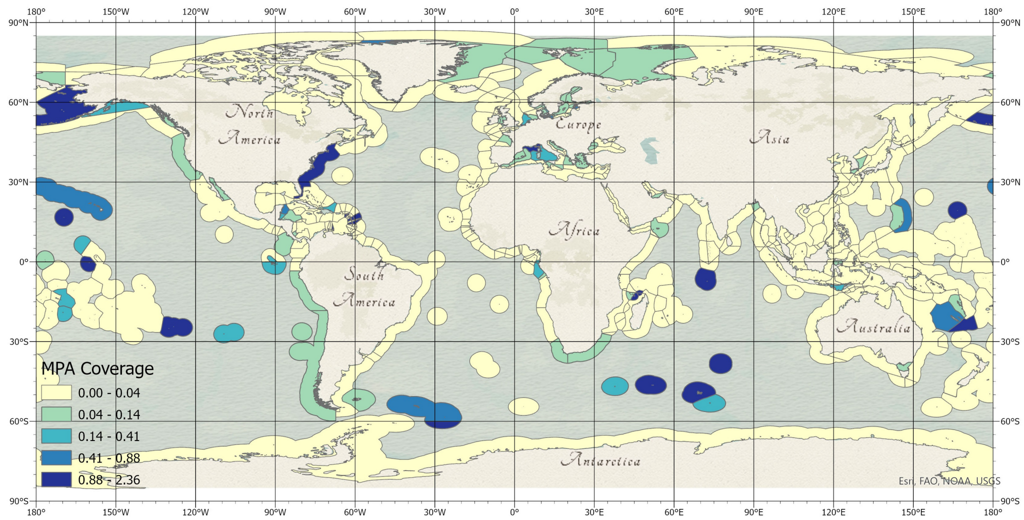
Finally, we include climatic and biological variables as control variables. The data were compiled at the grid level with a resolution of 0.1 degrees, based on the data reported by MODIS Aqua Ocean Color Data (NASA Goddard Space Flight Center and Group, 2018). The biological variables used are chlorophyll 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 biological 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.

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

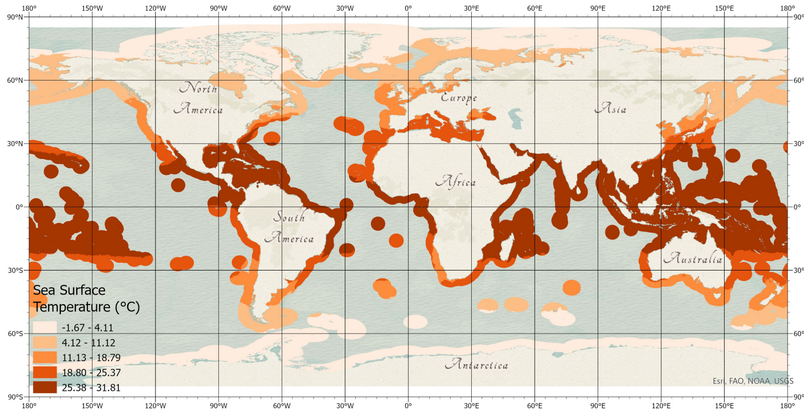


(a) *Geography of Marine Protected Areas by levels of protection*

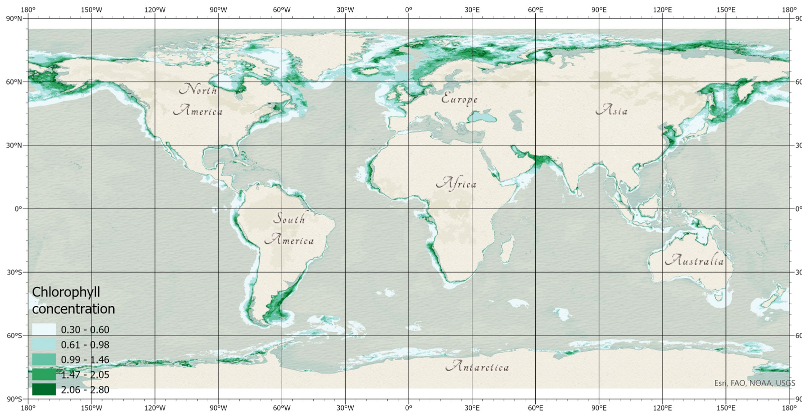


(b) *Marine Protected Areas Coverage*

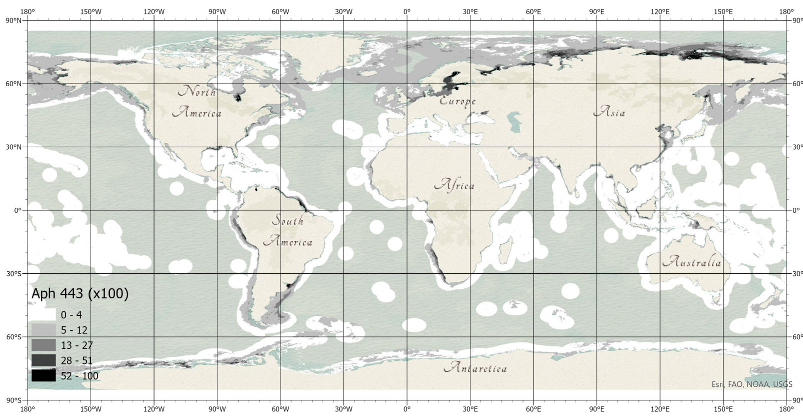
Figure 3. Marine Protected Areas Map. Source: Author, using information from Protected Seas and Marine Regions Repository. Note: Panel A shows the distribution of MPAs established before 2017 that are located within EEZs, and also displays the distribution according to the level of fishing protection based on the measurement by Protected Seas. Panel B shows the proportion of each EEZ's area that is protected by MPAs.



(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. Panel A shows the average sea surface temperature in degrees Celsius for each grid between 2017 and 2019. Panel B shows the average chlorophyll concentration for each grid between 2017 and 2019. Panel C presents the average phytoplankton absorption coefficient, rescaled between 0 and 100, for the period 2017-2019 for each grid.

2.6 Descriptive Statistics

Table 1 presents the descriptive statistics of the main variables in dataset for the period 2017–2019. On average, 746.5 fishing hours per 1,000 km^2 in period 2017-2019 were observed, with the presence of approximately 743 vessels. Based on SAR data, 53 publicly tracked vessels were detected per 1,000 km^2, along with an average of 22.4 non-publicly tracked vessels. Additionally, the table provides descriptive statistics for biological 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 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 km2	1,585,595	746.5	9,151	0	0	1,254,260
Vessels detection using AIS per 1000 km2	1,585,595	743.4	8,623	0	9.52	1,693,629
Unique Vessels detection using AIS per 1000 km2	1,585,595	213.8	1,134	0	9.17	139,692
Vessels detection using SAR per 1000 km2	1,585,595	52.99	517.0	0	0	73,163
Unique Vessels detection using SAR per 1000 km2	1,585,595	52.99	517.0	0	0	73,163
Unseen vessel detection using SAR per millon km2	1,585,595	22.41	203.0	0	0	24,926
Pr(Unseen vessel detection using SAR)	1,585,595	0.14	0.34	0	0	1
Climate and biological variables						
Sea surface temperature (°C)	1,517,276	15.25	11.45	-1.8	16.12	37.72
Chlorophyll concentration	918,075	0.86	2.03	0.002	0.29	81
Phytoplankton absorption	913,917	1.36	2.26	0.004	0.79	100
Grid characteristics						
Distance to MPAs boundary (km)	1,585,595	490	706	3,572	238	396
Distance to Ports (km)	1,585,595	687	932	0	334	4,741
Distance to shore (km)	1,585,595	160	118	0	147	909
Distance to Seamounts (m)	1,585,595	328,873	398,577	77.32	159,043	2,651,093
Distance to Pïracy events (m)	1,585,595	1,948,268	1,684,356	381	1,527,201	6,416,163
Depth (m)	1,585,595	-1,682	1,216	-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 average for period from 2017 to 2019.

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).

To address the problem of bias, we employ a Regression Discontinuity Design, which restrict the sample to observations closest 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 grids just outside the MPA. Each grid counts information on industrial fishing activity (Table 1). The effect is estimated using the model proposed by Calonico et al. (2014), which selects the optimal bandwidth (η) and computes the conditional mean difference between grids located inside (y_i^1) and outside (y_i^0) of protected areas right at the boundary z_o (Eq. 1). To assess the robustness of the estimates, we 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, τ, captures the average effect on global fishing activity per 1,000 km^2 during the study period 2017 - 2019.

$$\begin{aligned} \tau \quad &= \lim_{\eta \to 0} \mathbb{E}(y_i | z_i = z_0 + \eta) - \lim_{\eta \to 0} \mathbb{E}(y_i | z_i = z_0 - \eta) \\ &= \lim_{\eta \to 0} \mathbb{E}(y_i^1 | z_i = z_0 + \eta) - \lim_{\eta \to 0} \mathbb{E}(y_i^0 | z_i = z_0 - \eta) \\ &= \mathbb{E}(y_i^1 - y_i^0 | z_i = z_0) \\ &= \tau_{z_0} \end{aligned} \tag{1}$$

All regressions control for depth, sea surface temperature, Chlorophyll concentration, Phytoplankton absorption coefficient, distance to the shore, distance to ports, distance to piracy events, and distance to seamounts, and it is also controlled by a polynomial of order k of the distance to the MPA border. A linear polynomial will be used to avoid issues associated with higher-order polynomials, such as sensitivity to polynomial order and overly narrow confidence intervals (Gelman and Imbens, 2019).

The main assumption of the model is that confounders vary smoothly at the cutoff (Eq. 2), which we test using the permutation test of continuous distribution of covariates proposed by Canay and Kamat (2018).

[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).

$$\lim_{\eta \to 0} \mathbb{E}(y_i^j | z_i = z_0 + \eta) = \lim_{\eta \to 0} \mathbb{E}(y_i^j | z_i = z_0 - \eta) \text{ para } j \in 1, 0 \quad (2)$$

The results of the permutation test are presented in Table 2 (Table A2 presents test by levels of protections). 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]

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*
Sea surface temperature (°C)	*15.15*	*10.86*	*15.26*	*11.51*	*0.04*	*0.28*
Chlorophyll concentration	*0.75*	*1.99*	*0.87*	*2.03*	*0.04*	*0.29*
Phytoplankton absorption	*1.16*	*1.48*	*1.38*	*2.33*	*0.09*	*0.06*
Depth (m)	*-1718.42*	*1184.65*	*-1677.81*	*1218.67*	*0.05*	*0.24*
Distance to Shore (km)	*176.45*	*125.87*	*158.46*	*116.63*	*0.04*	*0.28*
Distance to Ports (km)	*832.57*	*893.86*	*672.03*	*934.77*	*0.12*	*0.02*
Distance to Seamounts (km)	*180.6*	*218.0*	*344.2*	*409.7*	*0.02*	*0.72*
Distance to Piracy Events (km)	*2119.2*	*1208.7*	*1930.6*	*1725.0*	*0.03*	*0.4*
Joint test					*0.16*	*0.08*

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Columns 1-4 present the descriptive statistics of cells of the nearest MPA boundary. The columns 5-6 presents the test statistic and p-value of the Canay and Kamat (2018) permutation test of continuous distribution of covariates at the cutoff.

We estimate the heterogeneous effects of MPA size, distance to the coast and ports, as well as distance to piracy events and biological fishing conditions. These estimates serve as an approach to understanding the relationship between law enforcement and MPA effectiveness, as well as to gain insights into some of the motivations behind fishers' decision-making on where to fish. These estimates are conducted using separate non-parametric regressions.

4 Results

In this section, we present the results on the effectiveness of MPAs in reducing fishing activity within their boundaries. We consider different levels of fishing protection to assess whether stricter restrictions enhance effectiveness. Additionally, we analyze how observable factors such as MPA size, distance to shore, ports, piracy events, and fishing conditions influence MPA effectiveness and fisher compliance.

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,

[5] The results for MPAs with protection levels of 4 should be interpreted with caution, as the joint test rejects the null hypothesis of continuously distributed covariates at the cutoff (Table A2).

conventional, bias-corrected, and robust estimates as proposed by Calonico et al. (2014) are reported.

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).

Considering this strategic behavior, our preferred specification is the conventional estimate with a donut hole approach to reduce the potential interdependence of observations inside and just outside the MPA boundaries. MPAs are established to conserve biodiversity and ecosystems within their designated areas. If successful, they increase the available biomass, which, assuming species mobility, leads to biomass spillover beyond the protected areas, increasing fish availability for legal fishing (Cuervo-Sánchez et al., 2018). However, if more vessels decide to fish within MPAs, the available fish stock outside the protected area decreases, creating incentives to increase fishing efforts both outside (to maintain at least constant catches) and inside the MPA due to lower availability beyond its borders. By removing the observations closest to the boundary (donut hole), this interdependence is expected to decrease. Nevertheless, other estimates are included for the sake of transparency.

According to the results reported in Table 3, MPAs reduce the number of vessels detected within their boundaries by 278.8 vessels per 1,000 km^2. In terms of fishing effort, MPAs are also effective in reducing total fishing hours within their boundaries by 712.3 hours per 1,000 km^2. However, note that at the optimal bandwidth, the strong interdependence among observations explains the lack of statistical significance. This result is linked to the strategic behavior of vessels around MPA borders, which influences the distribution of fishing effort across different areas.

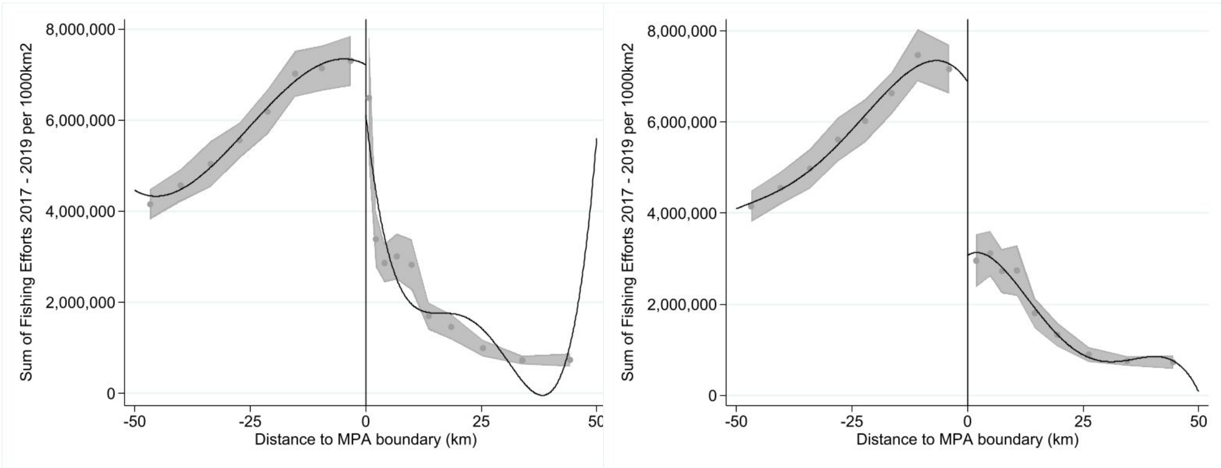
To validate the sensitivity of the results, we estimate the regressions for bandwidths ranging from 5km to 50km, and the coefficients are consistent and remain negative (Figure A6). Additionally, as an extra robustness check, we run the regressions using a placebo for the MPA boundary, and it is observed that the negative and significant effect is concentrated around the true cutoff point (Figure A7).

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	-445.9	-1,005.2***	-712.3**	-180.7***	-366.6***	-278.8***
	(281.8)	(133.3)	(345.9)	(59.63)	(23.91)	(78.26)
Bias-corrected	-364.6	-517.6***	-594.7*	-159.5***	-292.2***	-251.7***
	(281.8)	(133.3)	(345.9)	(59.63)	(23.91)	(78.26)
Robust	-364.6	-517.6**	-594.7	-159.5**	-292.2***	-251.7***
	(329.3)	(203.3)	(402.2)	(65.62)	(35.40)	(89.71)
Bandwidth (km)	13.84	50	12.71	8.09	50	11.73
Observations	129,194	911,869	122,201	129,194	911,869	122,201

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. We present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

Table 4 presents the results for AIS data across different protection levels of MPAs. We 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.



***(a)** Fishing hours*

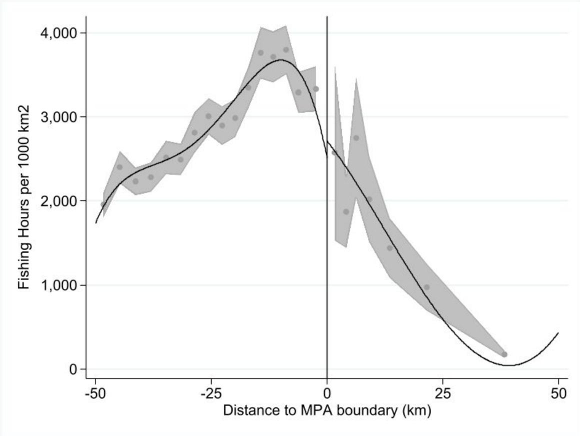
***(b)** Fishing hours: Donut hole 2km*

Figure 5. Regression discontinuity effect of MPAs on fishing activity using AIS data. Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: The left side of the figure shows the observations outside the MPAs, and the right side shows the observations inside the MPAs. The observations are binned according to the data-driven procedure IMSE-optimal quantile-spaced method using polynomial regression. The gray shading represents the confidence intervals at the 95% confidence level.

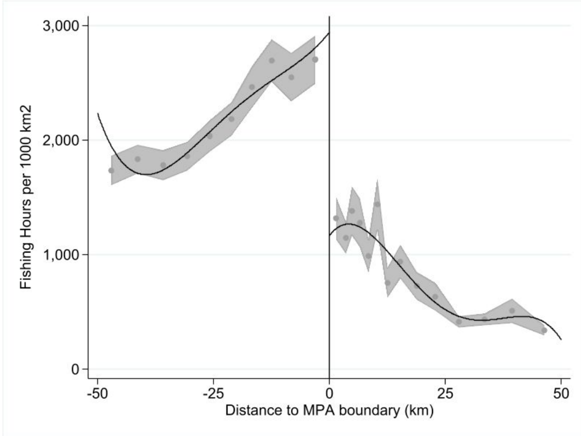
Table 4: *Regression discontinuity effect of MPAs on Fishing activity using AIS data by levels of protection*

	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 = Least restrictive						
Conventional	683.4	-885.2*	93.71	-201.9	-697.1***	-352.4*
	(887.7)	(473.4)	(1135)	(152.7)	(71.04)	(196.4)
Bias-corrected	960.6	203.5	514.7	-140.3	-537.7***	-251.7
	(887.7)	(473.4)	(1135)	(152.7)	(71.04)	(196.4)
Robust	960.6	203.5	514.7	-140.3	-537.7***	-251.7
	(1024.5)	(668.7)	(1355)	(167.3)	(102)	(222)
Bandwidth (km)	12.65	50	10.17	9.35	50	12.2
Observations	30,616	205,803	28,859	30,616	205,803	28,859
Level of protection = Less restrictive						
Conventional	-785.3**	-829.8***	-1276.7**	-187.4***	-115.3***	-193.9**
	(359.9)	(211.6)	(505.6)	(56.32)	(33.32)	(79.64)
Bias-corrected	-781.2**	-787.03***	-1421.6***	-204.4***	-168.2***	-216.5***
	(359.9)	(211.6)	(505.6)	(56.32)	(33.32)	(79.64)
Robust	-781.2*	-787.03**	-1421.6**	-204.4***	-168.2***	-216.5**
	(434.3)	(311.2)	(608.1)	(67.21)	(51.18)	(93.96)
Bandwidth (km)	17.69	50	16.31	20.03	50	15.57
Observations	42,428	237,240	39,827	42,428	237,240	39,827
Level of protection = Moderately restrictive						
Conventional	-546.2	-1121.8***	-1157.8*	-26.52	-245.1***	-34.34
	(552.2)	(261.3)	(674.3)	(52.29)	(26.26)	(103.5)
Bias-corrected	-394.03	-550.02**	-1127.7*	-7.24	-72.61***	3.36
	(552.2)	(261.3)	(674.3)	(52.29)	(26.26)	(103.5)
Robust	-394.03	-550.02	-1127.7	-7.24	-72.61*	3.36
	(671.6)	(419.2)	(891.9)	(58.47)	(37.94)	(119.1)
Bandwidth (km)	15.89	50	18.53	11.13	50	11.5
Observations	19,120	119,283	18,092	19,120	119,283	18,092
Level of protection = Heavily restrictive						
Conventional	-1055.8*	-1177***	-718.7	-354.2***	-349.8***	-463.3***
	(625.6)	(287.4)	(611.2)	(90.51)	(58.05)	(150.3)
Bias-corrected	-1137.9*	-962.01***	-634.9	-359.8***	-348.7***	-493.3***
	(625.6)	(287.4)	(611.2)	(90.51)	(58.05)	(150.3)
Robust	-1137.9	-962.01**	-634.9	-359.8***	-348.7***	-493.3***
	(817.5)	(475.9)	(756.7)	(110.5)	(90.14)	(178.9)
Bandwidth (km)	17.20	50	11.76	23.88	50	16.38
Observations	15,927	135,959	15,154	15,927	135,959	15,154
Level of protection = Most restrictive						
Conventional	-1572.2**	-1152.7***	-1112.3*	-58.45	-180.01***	-211.9*
	(710.6)	(293.6)	(578.9)	(104.7)	(50.35)	(122.7)
Bias-corrected	-1739.4**	-1350.5***	-1156.3**	-20.78	-154.4***	-200.1
	(710.6)	(293.6)	(578.9)	(104.7)	(50.35)	(122.7)
Robust	-1739.4**	-1350.5***	-1156.3	-20.78	-154.4*	-200.1
	(883.4)	(474.6)	(723.3)	(123.1)	(79.79)	(154.9)
Bandwidth (km)	13.48	50	16.36	16.02	50	17.4
Observations	21,086	213,497	20,252	21,086	213,497	20,252

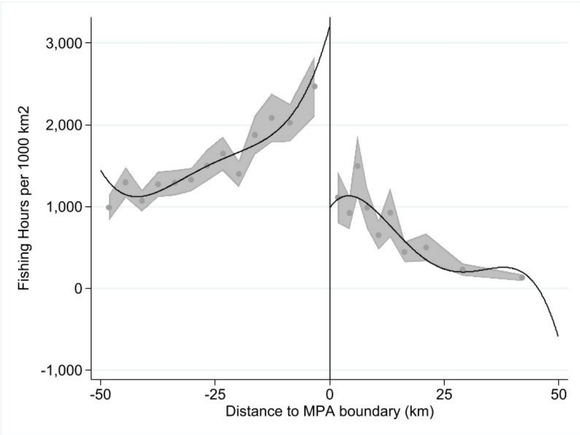
Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. Fishing hours is expressed in $hours/km^2$per1000. Calonico et al. (2014) RD estimate used with optimal bandwidth (columns 1, and 4), fixed 50 kms bandwidth (columns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



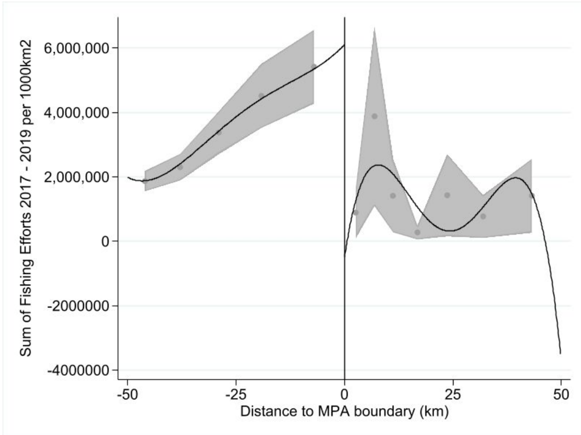
***(a)** Least restrictive*



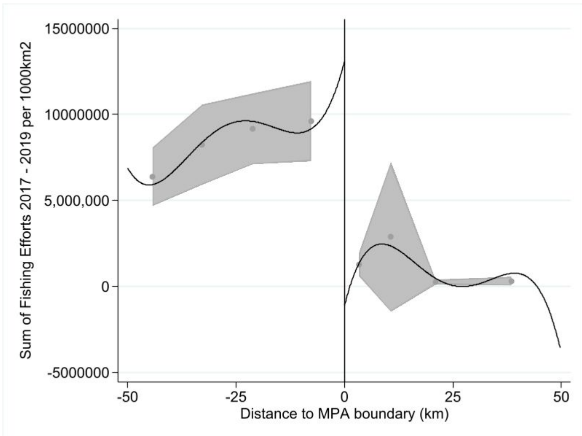
***(b)** Less restrictive*



***(c)** Moderately restrictive*



***(d)** Heavily restrictive*



***(e)** Most restrictive*

Figure 6. Regression discontinuity effect of MPAs on fishing activity using AIS data by levels of protection. Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: The left side of the figure shows the observations outside the MPAs, and the right side shows the observations inside the MPAs. The observations are binned according to the data-driven procedure IMSE-optimal quantile-spaced method using polynomial regression. The gray shading represents the confidence intervals at the 95% confidence level. All graphs present the estimates following the donut hole approach with a 2km exclusion zone.

When comparing the data from AIS and SAR, we 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).

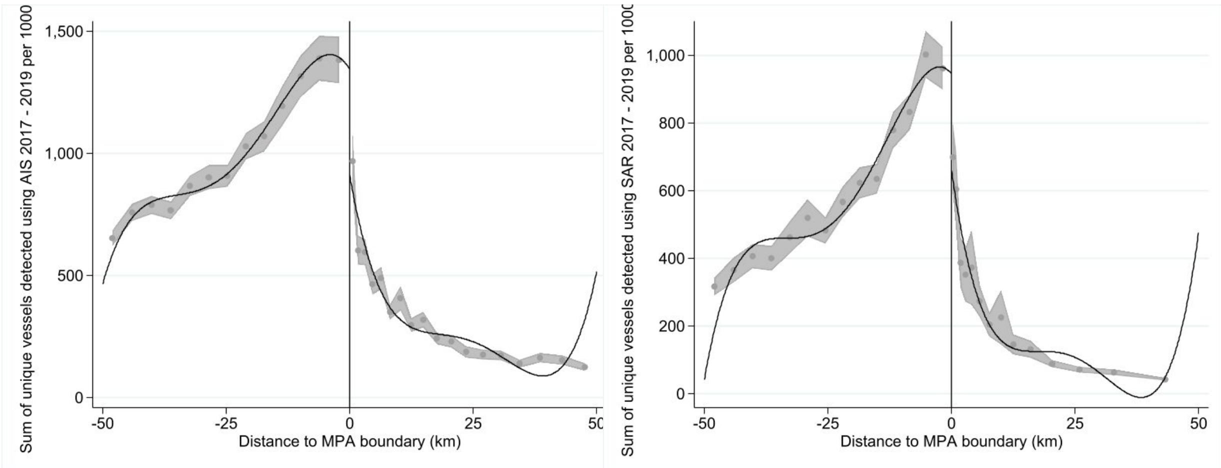
For different protection levels, Figures A3 and A4 display the RD plots for publicly and non-publicly tracked vessels, respectively. There is no evidence suggesting that higher protection levels lead to better outcomes in terms of reducing the number of both publicly and non-publicly tracked vessels (Table A4). As we also observed with the number of vessels detected using AIS data (Table 4). This unexpected result is reasonable given that MPAs with stricter fishing restrictions do not significantly reduce the number of vessels entering but do decrease the total fishing hours conducted within their boundaries. This suggests that vessels may still enter, but the greater enforcement effectiveness reduces the amount of time they spend fishing inside. One possible explanation is that vessels might have stronger incentives to enter highly restricted MPAs, perhaps due to higher fish stocks; however, we lack data to support this hypothesis.

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	-60.05	-190.1***	-236.2***
	(37.30)	(13.25)	(28.87)
Bias-corrected	-46.05	-187.5***	-247.3***
	(37.30)	(13.25)	(28.87)
Robust	-46.05	-187.5***	-247.3***
	(40.57)	(19.87)	(34.50)
Bandwidth (km)	6.21	50	19.13
Observations	129,194	911,869	122,201

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), fixed 50 kms bandwidth (columns 2), and 2km donut hole approach (columns 3). All regressions control for the climatic, physical and biological variables. We present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

Another possible explanation relates to the levels of fishing activity. As shown in Table A1, least restrictive MPAs exhibit, on average, higher fishing activity compared to most restrictive MPAs. When evaluating the extensive margin, i.e., the probability of detecting at least one non-publicly tracked vessel inside an MPA, we find that most restrictive MPAs reduce this probability by 14 percentage points (pp), whereas least restrictive MPAs reduce it by only 2 pp—although this result is not statistically significant.



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

Figure 7. Regression discontinuity effect of MPAs on fishing activity comparing AIS and SAR data. Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: The left side of the figure shows the observations outside the MPAs, and the right side shows the observations inside the MPAs. The observations are binned according to the data-driven procedure IMSE-optimal quantile-spaced method using polynomial regression. The gray shading represents the confidence intervals at the 95% confidence level.

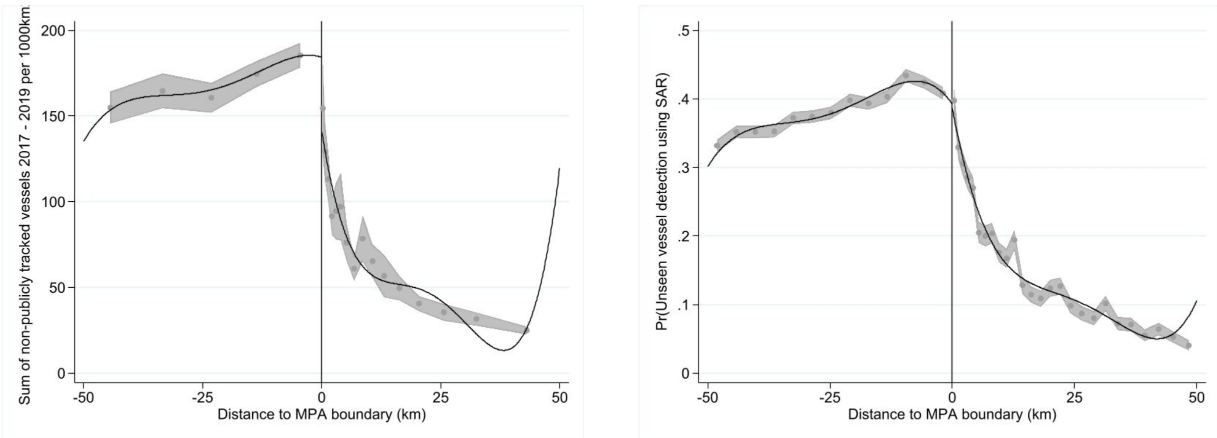
In general, for vessels not publicly tracked using SAR data, we observe that MPAs have been effective in reducing this type of "in the dark" activity (Park et al., 2020). Table 6 presents the results for the number of no-publicly tracked vessels and the likelihood of encountering such vessels. The estimates for the number of no-publicly tracked vessels are robust, indicating that MPAs have reduced this activity by approximately 31 vessels per km^2. However, when assessing the probability of finding at least one non-publicly tracked vessel within MPAs, we find that it increases by approximately 2 pp. This suggests that MPAs reduce fishing intensity in terms of the number of non-publicly tracked vessels within their boundaries. However, it is still more likely to find at least one non-publicly tracked vessel inside MPAs than outside. When analyzing these results by protection level, we observe that this outcome is driven by less restrictive MPAs (Table A4).

Figure 8 shows the RD plots for no-publicly tracked vessels, while Figures A5 display the RD plots for the probability for each protection level, respectively. In terms of probability to find at least one non-publicly tracked vessel, 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, in terms of the number of non-publicly tracked vessels, note that within MPAs, the dispersion of the data is considerably higher compared to the data outside the MPA (Figure A4), suggesting a greater presence inside.

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	-20.61***	-26.39***	-31.00****	0.03***	-0.02***	0.02*
	(4.45)	(2.22)	(5.11)	(0.01)	(0.005)	(0.02)
Bias-corrected	-19.25***	-22.69***	-31.43***	0.03***	0.004	0.03**
	(4.45)	(2.22)	(5.11)	(0.01)	(0.005)	(0.02)
Robust	-19.25***	-22.69***	-31.43***	0.03***	0.004	0.03*
	(5.15)	(3.37)	(6.43)	(0.01)	(0.007)	(0.02)
Bandwidth (m)	14.02	50	16.91	8.79	50	10.56
Observations	129,194	911,869	122,201	129,194	911,869	122,201

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. We 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. Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: The left side of the figure shows the observations outside the MPAs, and the right side shows the observations inside the MPAs. The observations are binned according to the data-driven procedure IMSE-optimal quantile-spaced method using polynomial regression. The gray shading represents the confidence intervals at the 95% confidence level.

4.1 Law Enforcement and Marine Conservation

The ability of MPAs to reduce fishing activity within their boundaries relies on law enforcement through the monitoring, control, and surveillance of protected areas (Gill et al., 2017). In a maritime context, it is reasonable to expect that the farther a protected area is from the shore or ports, the less effective it will be due to reduced accessibility (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. Our findings confirm that MPAs located closer to the shore have a greater effect in reducing fishing activity within their boundaries compared to those farther away, particularly in terms of the number of vessels (Table A5). These results hold when using SAR data as well (Table A6).

Tables A7 and A8 present the results concerning distance to ports, which are similar to those found for distance to the shore. MPAs that are closer to ports show a greater reduction in fishing activity, both when detected using SAR and AIS data. Notably, the observed reductions are even larger than those related to shore distance, which makes sense considering that maritime operations are primarily concentrated around ports rather than along the coastline.

Another factor that has drawn attention in the literature is MPA size (Albrecht et al., 2021, Friedlander et al., 2017, Edgar et al., 2014, Claudet et al., 2008). Larger protected areas may contribute to greater species and ecosystem conservation, proportional to the area's size. However, larger MPAs may also make monitoring and enforcement more challenging. Tables A9 and A10 present the results based on MPA size. We find that larger MPAs are effective in reducing fishing activity within their boundaries, both in terms of total fishing efforts and the number of vessels entering. This result suggests that, despite the greater difficulty in monitoring and enforcement associated with larger MPAs, the managing institutions have been effective in overseeing these larger areas. Additionally, we find that both larger and smaller MPAs are effective in reducing the number of non-publicly tracked vessels. However, larger MPAs decrease the probability of encountering non-publicly tracked vessels, while in smaller MPAs, this probability increases.

4.1.1 Piracy and Fishing Conditions zones

The decision-making process for fishers regarding where to fish is complex. However, like any economic activity, part of this process is driven by profit maximization, which primarily depends on maximizing catch per unit effort. Fishers seek to operate in areas with a higher probability of encountering abundant fish stocks, depending on their target species. Evaluating this relationship between fishing activity and fish stocks presents a challenge due to the lack of globally and temporally comprehensive data. However, the availability of environmental and biological geospatial data allows us to approximate this relationship. Axbard (2016) proposes using satellite imagery to estimate a measure of favorable fishing conditions based on sea surface temperature and phytoplankton concentration, which, when within specific thresholds, are associated with higher fish stocks as they create optimal conditions for fish reproduction and survival.

When evaluating MPA effectiveness based on the number of years (2017–2019) a grid has had favorable fishing conditions, we find that fishing efforts decrease within MPAs that have not had good fishing conditions or have only had them for one year—in other words, the less productive MPAs. In contrast, no significant effects are observed in MPAs that had favorable fishing conditions for at least two of the three years, meaning the more productive MPAs (Table A11).

At the same time, in the fishing decision-making process, fishers aim to minimize risks and costs associated with fishing operations. In this study, we assess risk associated to piracy activities, which is associated with political instability, lack of governance capacity, geography, and economic marginalization (Galgano, 2024). Moreover, piracy poses not only a direct threat to fishers but also a challenge to MPA management authorities, potentially jeopardizing conservation objectives.

Figure 9 displays global patterns of piracy incidents and fishing efforts. It shows that regions with lower AIS-detected fishing activity tend to overlap with areas of frequent piracy events. Conversely, these regions also exhibit higher SAR-detected activity, suggesting that fishing vessels in piracy-prone areas are more likely to disable their tracking devices to avoid detection. In terms of proximity to piracy hotspots, piracy appears to deter industrial fishing rather than encourage it, contradicting the assumption that lower enforcement would attract more fishing activity. These findings should be considered informative rather than causal. Future research should focus on establishing causal links between piracy and fishing behavior.

Evaluating these relationships, no significant differences are generally observed between AIS and SAR data. However, when focusing on the Central Caribbean, the Horn of Africa, and Indonesia, it becomes clear that these regions represent hotspots for the detection of non-publicly tracked vessels (Welch et al., 2022). These areas also exhibit the lowest AIS detection rates, the highest prevalence of piracy events, and the most favorable fishing conditions (Figure 9).

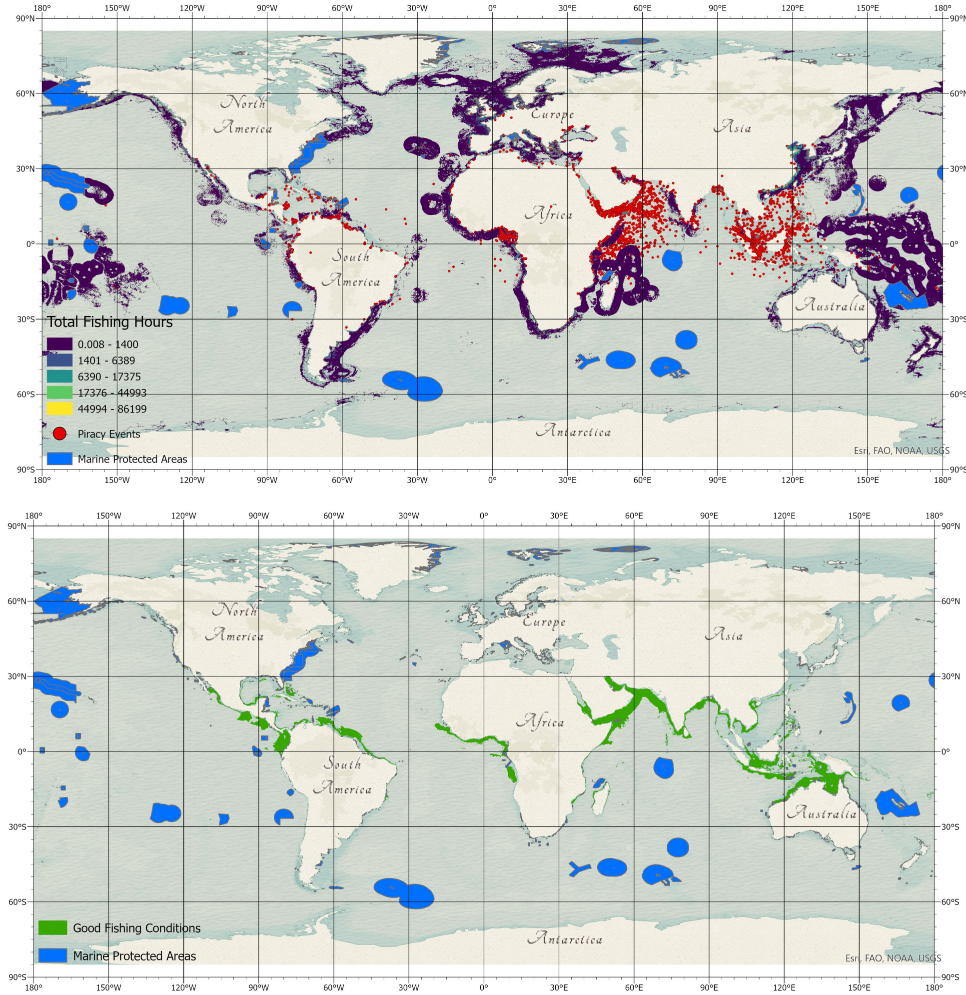


Figure 9. Piracy, Fishing conditions and Industrial Fishing in MPAs. Figure a) show piracy events, detected fishing activity using AIS and MPAs, and figure b) show areas with better fishing conditions. Note: Fishing conditions are calculated based on sea surface temperature and chlorophyll concentration (Axbard, 2016).

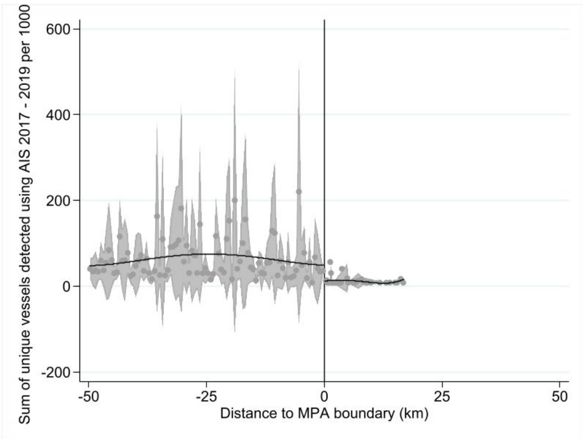
Figure 10 compares vessel detection using AIS and SAR data around MPAs in the Central Caribbean, the Horn of Africa, and Indonesia. Based on AIS data alone, one might conclude that fishing activity within MPAs is very low. However, SAR data reveals a significantly different picture, highlighting undetected activity in these regions.

Table 7 presents the estimates for the Central Caribbean, the Horn of Africa, and Indonesia regions. No significant evidence is found when using AIS data, whereas significant effects are detected using SAR data. Despite these differences, the results consistently indicate that MPAs effectively reduce fishing activity within their boundaries. When generalizing the analysis, we find no significant effects in MPAs located near regions with a high prevalence of piracy events, except for the number of vessels detected using SAR data. In contrast, for MPAs farther from these piracy-prone regions, the effectiveness of MPAs in controlling fishing activity becomes evident (Table A12). We can notice that areas affected by piracy generate a deterrent effect on industrial activity, which in itself contributes to the greater effectiveness of MPAs, and not the opposite, since higher piracy activity could indicate weak institutional enforcement. Furthermore, these findings emphasize the importance of accurately detecting fishing activity to ensure clear and transparent policy insights.

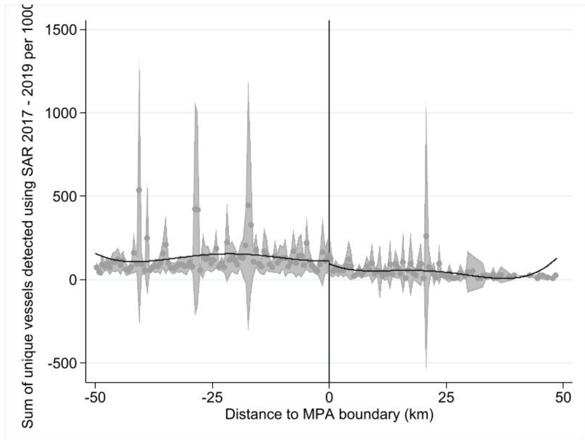
Table 7: *Regression discontinuity effect of MPAs on fishing activity comparing AIS and SAR data in the High Piracy and Good Fishing Condition Zones*

	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	-3.40	-7.73**	-4.03	-23.94	-81.97***	21.68	-66.46**	-63.62***	-117.1**
	(2.72)	(3.01)	(6.03)	(32.79)	(19.91)	(30.29)	(27.23)	(16.71)	(55.14)
Bias-corrected	-3.19	-2.09	-3.82	-28.33	-48.65**	30.90	-69.44**	-63.28***	-127.8**
	(2.72)	(3.01)	(6.03)	(32.79)	(19.91)	(30.29)	(27.23)	(16.71)	(55.14)
Robust	-3.19	-2.09	-3.82	-28.33	-48.65*	30.90	-69.44**	-63.28**	-127.8*
	(2.97)	(3.98)	(6.73)	(37.98)	(25.68)	(34.9)	(31.89)	(24.82)	(65.69)
Bandwidth (m)	13.05	50	12.52	10.15	50	10.29	18.50	50	10.66
Observations	3,709	29,543	3,498	3,709	29,543	3,498	3,709	29,543	3,498

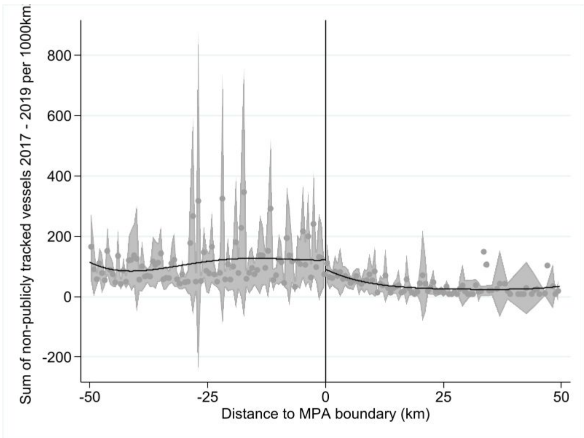
Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. Calonico et al. (2014) RD estimate used with optimal bandwidth (columns 1, 5 and 7), fixed 50 kms bandwidth (columns 2, 6 and 8), and 2km donut hole approach (columns 3, 7 and 9). All regressions control for the climatic, physical and biological variables. We 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*



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

Figure 10. Regression discontinuity effect of MPAs on fishing activity comparing AIS and SAR data in the High Piracy and Good Fishing Condition Zones. Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: The left side of the figure shows the observations outside the MPAs, and the right side shows the observations inside the MPAs. The observations are binned according to the data-driven procedure IMSE-optimal quantile-spaced method using polynomial regression. The gray shading represents the confidence intervals at the 95% confidence level.

5 Conclusions

This paper evaluates the effectiveness of MPAs in reducing industrial fishing activity on a global scale. To achieve this, we use 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. We propose a Regression Discontinuity model that addresses selection bias issues by controlling for observable and unobservable characteristics, allowing for causal estimates. Using this model, we estimate the reduction in fishing activity within MPAs according to the level of fishing protection. Additionally, to gain deeper insight into fishers' motivations, we examine potential factors explaining changes in fisher compliance, such as the influence of MPA size, distance to the shore, ports, and piracy events, and the shifts in biological conditions favorable to fishing.

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 regions such as Indonesia, the Horn of Africa, and the Central Caribbean, regions characterized as a hotspot for non-publicly tracked vessels (Paolo et al., 2024). We find that there is no evidence suggesting that higher protection levels lead to better outcomes in terms of reducing the number of both publicly and non-publicly tracked vessels. This unexpected result is reasonable given that MPAs with stricter fishing restrictions do not significantly reduce the number of vessels entering but do decrease the total fishing hours conducted within their boundaries. This suggests that vessels may still enter, but the greater enforcement effectiveness reduces the amount of time they spend fishing inside. One possible explanation is that vessels might have stronger incentives to enter highly restricted MPAs, perhaps due to higher fish stocks.

We also find that, on average, fishing activity increases near the borders of MPAs, providing empirical evidence of a positive spillover effect[6]. 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, we find that MPAs closer to the shore are more effective in reducing fishing activity within their boundaries compared to those farther away, particularly in terms of the number of vessels. These results remain consistent when using SAR data. According to distance to ports, MPAs located closer to ports show a greater

[6] As discussed in the results section, this increase may be due to the activity found within the MPAs. However, the decline inside is significantly greater, leading us to assume that this increase just outside is more likely driven by the exploitation of the positive spillover effect generated by greater conservation rather than by compensating for reduced availability due to activity within the MPAs.

reduction in fishing activity, both when detected through SAR and AIS data. Notably, these reductions are even larger than those related to shore distance. In terms of MPA size, we observe that larger MPAs are effective in reducing fishing activity within their boundaries, both in terms of total fishing efforts and the number of vessels entering. This result suggests that, despite the greater difficulty in monitoring and enforcement associated with larger MPAs, the managing institutions have been effective in overseeing these larger areas.

Furthermore, considering that fishermen base their decisions on where to fish according to biological conditions conducive to fishing (Bos, 2021, Axbard, 2016, Flückiger and Ludwig, 2015), we find that fishing efforts decrease within MPAs with poor fishing conditions or those that had favorable conditions for only one year—in other words, the less productive MPAs. In contrast, no significant effects are observed in MPAs with favorable fishing conditions for at least two of the three years (2017–2019), meaning the more productive MPAs. Finally, in regions with a history of piracy events, AIS detection of industrial activity is lower, while SAR detection is higher, suggesting that fishermen may disable their transmitters to avoid detection by pirates (Welch et al., 2022). We find no significant effects in MPAs near regions with high piracy prevalence, except for the number of vessels detected using SAR data. In contrast, for MPAs farther from piracy-prone regions, their effectiveness in controlling fishing activity is evident.

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 we 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. 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 suggest that MPAs are an effective tool in the fight against overfishing. Proper management and the appropriate use of monitoring and control tools play a crucial role in the effectiveness of MPAs. Although conservation restricts fishing activity in the short term, greater conservation creates medium-term incentives that help preserve and increase the availability of fish stocks for fishing. Additionally, the results of this article underscore the importance of using increasingly reliable and accurate data to improve the evaluation of conservation instruments, particularly in the marine context. Misuse or lack of data availability could lead to erroneous conclusions, potentially undermining conservation efforts. Furthermore, the study highlights the importance of effective enforcement in ensuring compliance with the conservation objectives of MPAs.

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Appendix. Theoretical Economic Model: Optimal Fishing Decision in MPAs

Model Assumptions

Consider a model where fishers seek to maximize their profits by choosing the amount of fishing effort E_i between two possible areas: inside an MPA (E_m) and outside the MPAs (E_o), where $E_i = E_m + E_o$. We assume that the fish stock or biomass size (B_m) is greater within the MPAs due to protection, which increases fishing productivity in that area.

Fishers incur a unit cost for each fishing effort $C(E_m, E_o)$. The unit cost of effort inside MPAs is higher due to the risk of sanctions. If a fisher is detected engaging in fishing activity within the MPA, they must pay a fine F. The probability of being caught $p(d_m)$ depends on the distance the vessel enters the protected area, meaning that the deeper they go into the area, the longer it takes to exit, and consequently, the probability of being caught increases. Then, the cost of being caught is $p(d_m)F$.

Fisher's Profit Function

The fisher's profit function is characterized as:

$$\Pi(E_m, E_o) = P[Q_m(E_m, B_m) + Q_o(E_o, B_o)] - C(E_m, E_o) - p(d_m)F$$

Where P is the market price of fish. $Q_m(E_m, B_m)$ represents the total fish catch inside MPAs, while $Q_o(E_o, B_o)$ represents catches outside MPAs. The functions $Q_m(.)$ and $Q_o(.)$ can be expressed as $\alpha B_m E_m$ and $\beta B_o E_o$, respectively, indicating the proportion of biomass captured per unit of effort. The cost function is expressed as $C(E_m, E_o) = c_m E_m + c_o E_o$. Finally, F is the fine for being detected, and $p(d_m)$ is the probability of being caught, which increases with d_m.

Profit-Maximizing Decision Making

The fisher chooses E_m and E_o to maximize Π. Deriving the first-order conditions, we obtain:

$$P\alpha B_m - c_m - p(d_m)F = 0$$

$$P\beta B_o - c_o = 0$$

Thus, the fisher will decide to fish within MPAs ($E_m > 0$) if:

$$P\alpha B_m - c_m > P\beta B_o - c_o + p(d_m)F$$

That is, if the productivity of fishing inside MPAs is high enough to compensate for the sanction costs.

Model Predictions

Regarding fishing restrictions, we observe that if $p(d_m)$ and F are sufficiently large, E_m will tend to zero. In other words, when protection levels are higher, the effectiveness of MPAs in reducing fishing activity within their boundaries will be greater. However, if B_m is significantly higher than B_o, fishers will have incentives to enter MPAs illegally, meaning that the high productivity of MPAs may limit their effectiveness due to the economic incentives for fishers.

In general terms, if $p(d_m)$ increases more rapidly with distance d_m, meaning that monitoring and enforcement tools are more effective, then the reduction of fishing efforts within MPAs (E_m) will be greater, making protected areas more effective. Thus, the larger size of MPAs forces vessels to travel greater distances to enter and exit, increasing the likelihood of capture $p(d_m)$. This, in turn, reduces incentives for illegal fishing E_m and enhances the effectiveness of protected areas.

Appendix. Additional Tables and Figures

Table A1. Descriptive statistics by levels of protection

	Levels of protections				
	Least restrictive	Less restrictive	Moderately restrictive	Heavily restrictive	Most restrictive
Outcome variables					
Fishing Hours per 1000 km2	1,187	568.6	138.3	59.74	94.45
Vessels detection using AIS per 1000 km2	1,603	728.1	202.4	74.23	97.36
Unique Vessels detection using AIS per 1000 km2	231.3	223.4	66.62	30.35	27.65
Vessels detection using SAR per 1000 km2	141.3	31.5	10.91	2.96	3.78
Unique Vessels detection using SAR per 1000 km2	141.3	31.5	10.91	2.96	3.78
Unseen vessel detection using SAR per millon km2	27.67	8.19	2.38	0.67	2.02
Pr(Unseen vessel detection using SAR)	0.32	0.13	0.04	0.01	0.01
Environmental conditions					
Sea surface temperature (°C)	18.95	11.22	10.03	20.34	21.69
Chlorophyll concentration	1.24	1.11	0.54	0.22	0.31
Phytoplankton absorption	1.23	1.62	1.14	0.46	0.64
Grid characteristics					
Distance to MPAs boundary (km)	24.58	89.59	105.10	62.23	68.32
Distance to Ports (km)	542.9	335.9	2,018.90	919.80	785
Distance to Shore (km)	114.8	166.6	182.24	190.80	196.13
Distance to Seamounts (m)	185,362	230,799	157,094	137,597	138,393
Distance to Pïracy events (m)	834,306	2,311,749	2,488,270	2,008,820	1,889,013
Depth (m)	-1,641	-1,658	-1,194	-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. Continuous distribution of baseline marine characteristics at MPAs borders by level of protection

	Treatment		Control		Permutation test	
	Mean	*Std.Dev*	*Mean*	*Std.Dev*	*t-test*	*p-value*
Levels of protection = Least restrictive						
Sea surface temperature (°C)	*18.95*	*9.59*	*19.30*	*9.53*	*0.04*	*0.25*
Chlorophyll concentration	*1.24*	*3.42*	*0.93*	*2.40*	*0.02*	*0.77*
Phytoplankton absorption	*1.23*	*2.28*	*1.25*	*1.87*	*0.03*	*0.45*
Depth (m)	*-1641.11*	*1544.88*	*-1649.77*	*1289.08*	*0.02*	*0.64*
Distance to Shore (km)	*114.81*	*115.31*	*154.44*	*114.99*	*0.15*	*0.05*
Distance to Ports (km)	*542.87*	*688.62*	*350.96*	*617.97*	*0.11*	*0.03*
Distance to Seamounts (km)	*185.4*	*285.8*	*318.2*	*409.9*	*0.03*	*0.5*
Distance to Piracy Events (km)	*834.3*	*859.8*	*1003.7*	*1091.3*	*0.02*	*0.73*
Joint test					*0.15*	*0.13*
Levels of protection = Less restrictive						
Sea surface temperature (°C)	*11.22*	*10.18*	*13.56*	*11.05*	*0.02*	*0.65*
Chlorophyll concentration	*1.11*	*2.11*	*1.15*	*2.34*	*0.06*	*0.12*
Phytoplankton absorption	*1.62*	*1.68*	*1.87*	*3.29*	*0.07*	*0.08*
Depth (m)	*-1658.04*	*1158.29*	*-1621.47*	*1189.74*	*0.05*	*0.19*
Distance to Shore (km)	*166.65*	*114.52*	*166.79*	*126.65*	*0.04*	*0.27*
Distance to Ports (km)	*335.91*	*263.88*	*614.92*	*708.58*	*0.07*	*0.09*
Distance to Seamounts (km)	*230.8*	*238.0*	*397.1*	*401.9*	*0.03*	*0.44*
Distance to Piracy Events (km)	*311.7*	*1455.6*	*2149.2*	*1684.4*	*0.03*	*0.46*
Joint test					*0.16*	*0.05*
Levels of protection = Moderately restrictive						
Sea surface temperature (°C)	*10.03*	*7.87*	*15.84*	*11.19*	*0.05*	*0.22*
Chlorophyll concentration	*0.54*	*1.37*	*0.78*	*1.78*	*0.02*	*0.65*
Phytoplankton absorption	*1.14*	*1.10*	*1.33*	*1.92*	*0.01*	*0.94*
Depth (m)	*-1194.37*	*924.47*	*-1654.91*	*1124.32*	*0.06*	*0.13*
Distance to Shore (km)	*182.24*	*126.41*	*170.74*	*107.25*	*0.01*	*0.96*
Distance to Ports (km)	*2018.87*	*1190.27*	*599.08*	*977.31*	*0.02*	*0.77*
Distance to Seamounts (km)	*157.1*	*142.1*	*262.6*	*313.3*	*0.14*	*0.01*
Distance to Piracy Events (km)	*2488.3*	*908.2*	*1530.8*	*1533.7*	*0.06*	*0.14*
Joint test					*0.15*	*0.07*
Levels of protection = Heavily restrictive						
Sea surface temperature (°C)	*20.34*	*10.89*	*16.32*	*12.77*	*0.09*	*0.06*
Chlorophyll concentration	*0.22*	*0.91*	*0.71*	*1.67*	*0.16*	*0.00*
Phytoplankton absorption	*0.46*	*0.68*	*1.17*	*2.19*	*0.09*	*0.05*
Depth (m)	*-2227.29*	*1238.22*	*-1945.78*	*1184.41*	*0.1*	*0.04*
Distance to Shore (km)	*190.84*	*133.62*	*154.12*	*109.45*	*0.18*	*0.01*
Distance to Ports (km)	*919.84*	*560.84*	*440.27*	*271.51*	*0.13*	*0.01*
Distance to Seamounts (km)	*137.6*	*193.3*	*389.6*	*550.1*	*0.04*	*0.26*
Distance to Piracy Events (km)	*2008.8*	*792.8*	*1784.3*	*1264.2*	*0.05*	*0.21*
Joint test					*0.18*	*0.04*
Levels of protection = Most restrictive						
Sea surface temperature (°C)	*21.69*	*8.81*	*11.94*	*11.57*	*0.03*	*0.45*
Chlorophyll concentration	*0.31*	*1.95*	*0.67*	*1.51*	*0.04*	*0.27*
Phytoplankton absorption	*0.64*	*0.81*	*1.18*	*1.70*	*0.02*	*0.59*
Depth (m)	*-1860.79*	*1045.38*	*-1589.48*	*1226.09*	*0.01*	*0.9*
Distance to Shore (km)	*196.13*	*134.86*	*150.64*	*115.83*	*0.09*	*0.09*
Distance to Ports (km)	*785.03*	*693.06*	*1202.97*	*1326.65*	*0.1*	*0.04*
Distance to Seamounts (km)	*138.4*	*208.3*	*324.0*	*330.2*	*0.03*	*0.43*
Distance to Piracy Events (km)	*1889.0*	*964.9*	*2823.5*	*2054.8*	*0.05*	*0.23*
Joint test					*0.1*	*0.3*

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Columns 1-4 present the descriptive statistics of cells of the nearest MPA boundary. The columns 5-6 presents the test statistic and p-value of the Canay and Kamat (2018) permutation test of continuous distribution of covariates at the cutoff.

Table A3. 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.

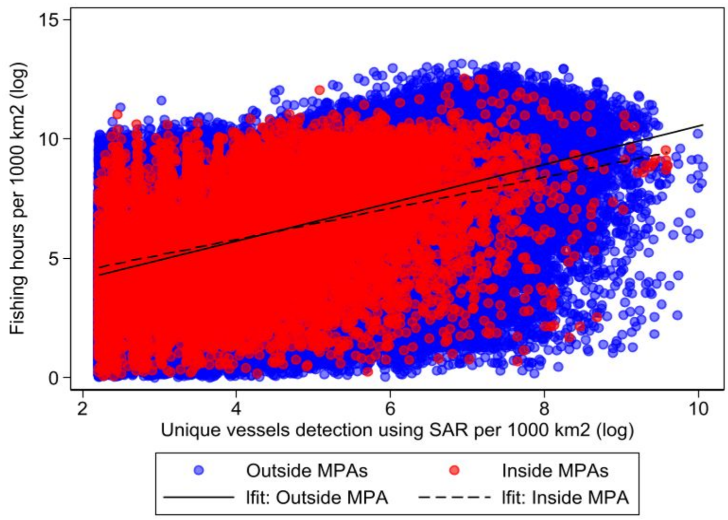


Figure A1. Correlation of AIS Fishing Hours and SAR Vessel Detections. Source: Authors' calculations based on data from GFW, and ProtectedSeas. The figure presents the relationship between the predicted number of fishing activity hours using AIS data and the number of vessels detected using SAR data between 2017 and 2019 for the entire sample. Each point represents a grid cell.

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 = Least restrictive									
Conventional	-129.7	-313.3***	-411.4***	-18.69	-57.99***	-88.94***	0.05**	-0.02*	-0.02
	(80.19)	(35.68)	(82.02)	(14.16)	(6.19)	(11.45)	(0.02)	(0.01)	(0.03)
Bias-corrected	-96.85	-316.2***	-421.7***	-12.25	-51.52***	-89.55***	0.06**	-0.002	-0.02
	(80.19)	(35.68)	(82.02)	(14.16)	(6.19)	(11.45)	(0.02)	(0.01)	(0.03)
Robust	-96.85	-316.2***	-421.7***	-12.25	-51.52***	-89.55***	0.06**	-0.002	-0.02
	(87.63)	(51.72)	(96.78)	(15.63)	(8.99)	(13.59)	(0.03)	(0.02)	(0.03)
Bandwidth (km)	8.32	50	16.03	8.92	50	17.42	8.68	50	15.12
Observations	30,616	205,803	28,859	30,616	205,803	28,859	30,616	205,803	28,859
Level of protection = Less restrictive									
Conventional	-96.47**	-169.8***	-229.04***	0.02	-10.85***	-1.92	0.05***	0.04***	0.06***
	(45.41)	(21.56)	(46.85)	(4.77)	(3.17)	(8.21)	(0.02)	(0.007)	(0.02)
Bias-corrected	-79.53*	-157.1***	-237.7***	0.90	-1.80	0.41	0.05***	0.05***	0.06***
	(45.41)	(21.56)	(46.85)	(4.77)	(3.17)	(8.21)	(0.02)	(0.007)	(0.02)
Robust	-79.53	-157.1***	-237.7***	0.90	-1.80	0.41	0.05***	0.05***	0.06***
	(51.86)	(31.02)	(58.3)	(5.54)	(4.32)	(9.46)	(0.02)	(0.01)	(0.02)
Bandwidth (km)	11.02	50	18.41	14.25	50	12.77	10.29	50	16.13
Observations	42,428	237,240	39,827	42,428	237,240	39,827	42,428	237,240	39,827
Level of protection = Moderately restrictive									
Conventional	-4.55	-63.05**	31.54	-26.36**	-21.16***	-30.73*	-0.03*	-0.05***	-0.03
	(48.59)	(26.44)	(118.5)	(10.26)	(5.52)	(17.28)	(0.02)	(0.01)	(0.03)
Bias-corrected	14.02	-44.22*	68.27	-30.43***	-23.57***	-37.21**	-0.03	-0.03***	-0.02
	(48.59)	(26.44)	(118.5)	(10.26)	(5.52)	(17.28)	(0.02)	(0.01)	(0.03)
Robust	14.02	-44.22	68.27	-30.43**	-23.57***	-37.21	-0.03	-0.03**	-0.02
	(53.84)	(39.62)	(145.8)	(12.99)	(9.43)	(22.84)	(0.02)	(0.01)	(0.04)
Bandwidth (km)	12.24	50	11.83	21.73	50	17.47	13.5	50	11.47
Observations	19,120	119,283	18,092	19,120	119,283	18,092	19,120	119,283	18,092
Level of protection = Heavily restrictive									
Conventional	-145.5***	-144.7***	-179.5***	-5.27	-9.24**	-14.44	-0.04***	-0.05***	-0.08***
	(41.44)	(23.92)	(55.05)	(6.53)	(4.41)	(11.71)	(0.02)	(0.008)	(0.02)
Bias-corrected	-141.9***	-161.9***	-186.6***	-3.96	-7.49*	-14.29	-0.04***	-0.05***	-0.08***
	(41.44)	(23.92)	(55.05)	(6.53)	(4.41)	(11.71)	(0.02)	(0.008)	(0.02)
Robust	-141.9***	-161.9***	-186.6***	-3.96	-7.49	-14.29	-0.04**	-0.05***	-0.08***
	(48.56)	(34.87)	(67.26)	(7.46)	(6.31)	(13.88)	(0.02)	(0.01)	(0.03)
Bandwidth (km)	15.19	50	19.74	20.41	50	16.29	16.01	50	13.55
Observations	15,927	135,959	15,154	15,927	135,959	15,154	15,927	135,959	15,154
Level of protection = Most restrictive									
Conventional	-148.2***	-141.4***	-164.5***	-28.18**	-24.94***	-38.44**	-0.12***	-0.14***	-0.14***
	(34.52)	(20.77)	(40.99)	(13.45)	(6.02)	(16.47)	(0.02)	(0.009)	(0.02)
Bias-corrected	-148.6***	-171.2***	-175.2***	-31.1**	-20.31***	-43.46***	-0.11***	-0.13***	-0.14***
	(34.52)	(20.77)	(40.99)	(13.45)	(6.02)	(16.47)	(0.02)	(0.009)	(0.02)
Robust	-148.6***	-171.2***	-175.2***	-31.1*	-20.31**	-43.46**	-0.11***	-0.13***	-0.14***
	(42.65)	(32.85)	(50.92)	(16.96)	(9.68)	(20.09)	(0.02)	(0.01)	(0.03)
Bandwidth (km)	21.89	50	19.52	14.9	50	11.28	11.53	50	13.38
Observations	21,086	213,497	20,252	21,086	213,497	20,252	21,086	213,497	20,252

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. We present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

Table A5. Regression discontinuity effect of MPAs on fishing activity by proximity to shore using AIS data

	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)
Distance to Shore <147km						
Conventional	-349.7	-937.3***	-558.8	-153.3**	-396.6***	-289.4***
	(325.9)	(165.6)	(387.1)	(70.84)	(28.47)	(85.85)
Bias-corrected	-261.4	-406**	-439.9	-128.2*	-299.8***	-256.6***
	(325.9)	(165.6)	(387.1)	(70.84)	(28.47)	(85.85)
Robust	-261.4	-406	-439.9	-128.2	-299.8***	-256.6***
	(379.6)	(247.2)	(461.4)	(78.09)	(41.93)	(98.82)
Bandwidth (km)	14.40	50	13.35	7.91	50	12.38
Observations	102,049	444,081	96,127	102,049	444,081	96,127
Distance to Shore >147km						
Conventional	-86.09	-189.7**	-250.5	-8.24	-24.77***	-10.74
	(137.01)	(78.77)	(251.8)	(9.26)	(4.89)	(13.34)
Bias-corrected	-65.85	-90.35	-255.4	-5.32	-11.94**	-7.72
	(137.01)	(78.77)	(251.8)	(9.26)	(4.89)	(13.34)
Robust	-65.85	-90.35	-255.4	-5.32	-11.94*	-7.72
	(169.8)	(116.3)	(315.5)	(10.94)	(7.04)	(16.09)
Bandwidth (km)	17.63	50	13.14	13.51	50	13.26
Observations	27,145	467,788	26,074	27,145	467,788	26,074

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. The 147 km represents the median of the distribution of distance to the shore. 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. We present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

Table A6. Regression discontinuity effect of MPAs on fishing activity by proximity to shore using SAR data

	Vessels detection using SAR per 1000 km2			*Unseen vessel detection using SAR per millon km2*			*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)
Distance to Shore <147km									
Conventional	-38.18	-191.9***	-231.1***	-20.53***	-23.47***	-28.67***	0.04***	0.002	0.04***
	(43.80)	(16.15)	(33.67)	(4.93)	(2.65)	(5.54)	(0.01)	(0.005)	(0.02)
Bias-corrected	-21.46	-185.5***	-238.8***	-19.37***	-20.45***	-29.24***	0.05***	0.02***	0.05***
	(43.80)	(16.15)	(33.67)	(4.93)	(2.65)	(5.54)	(0.01)	(0.005)	(0.02)
Robust	-21.46	-185.5***	-238.8***	-19.37***	-20.45***	-29.24***	0.05***	0.02***	0.05***
	(47.64)	(23.67)	(40.77)	(5.74)	(3.99)	(6.94)	(0.01)	(0.008)	(0.02)
Bandwidth (km)	13.62	50	20.08	15.47	50	18.23	8.82	50	12.31
Observations	102,049	444,081	96,127	102,049	444,081	96,127	102,049	444,081	96,127
Distance to Shore >147km									
Conventional	-1.01	-1.89	-2.17	-0.1	-0.19	0.68	0.02*	0.01**	0.03**
	(1.73)	(1.19)	(2.83)	(1.06)	(0.71)	(1.75)	(0.01)	(0.006)	(0.02)
Bias-corrected	-0.71	-1.21	-1.98	-0.198	-0.01	0.72	0.02**	0.02***	0.04***
	(1.73)	(1.19)	(2.83)	(1.06)	(0.71)	(1.75)	(0.01)	(0.006)	(0.02)
Robust	-0.71	-1.21	-1.98	-0.198	-0.01	0.72	0.02*	0.02*	0.04**
	(2.00)	(1.63)	(3.44)	(1.22)	(1.03)	(2.07)	(0.01)	(0.008)	(0.02)
Bandwidth (km)	17.37	50	16.21	21.89	50	18.4	15.63	50	14.69
Observations	27,145	467,788	26,074	27,145	467,788	26,074	27,145	467,788	26,074

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. The 147 km represents the median of the distribution of distance to the shore. 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. We present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

Table A7. Regression discontinuity effect of MPAs on fishing activity by proximity to ports using AIS data

	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)
			Distance to Ports <334km			
Conventional	-427.4	-976.2***	-628.7	-237.5***	-433.2***	-327.9***
	(345.1)	(180.3)	(410.3)	(72.14)	(30.29)	(87.8)
Bias-corrected	-343.8	-446.8**	-519.7	-213.5***	-343.9***	-293.9***
	(345.1)	(180.3)	(410.3)	(72.14)	(30.29)	(87.8)
Robust	-343.8	-446.8*	-519.7	-213.5***	-343.9***	-293.9***
	(406.5)	(268.3)	(491.4)	(80.07)	(44.48)	(101.3)
Bandwidth (km)	14.96	50	13.64	8.46	50	12.98
Observations	91,423	496,802	85,949	91,423	496,802	85,949
			Distance to Ports >334km			
Conventional	-12.99	-73.61***	15.52	0.89	-5.87***	-5.78*
	(25.19)	(14.52)	(34.75)	(3.26)	(1.42)	(2.98)
Bias-corrected	-4.79	-39.96***	26.48	2.04	-0.55	-5.55*
	(25.19)	(14.52)	(34.75)	(3.26)	(1.42)	(2.98)
Robust	-4.79	-39.96**	26.48	2.04	-0.55	-5.55
	(30.53)	(18.60)	(40.08)	(3.86)	(2.08)	(3.60)
Bandwidth (km)	11.99	50	8.81	9.97	50	14.72
Observations	37,771	415,067	36,252	37,771	415,067	36,252

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. The 334 km represents the median of the distribution of distance to the ports. 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. We present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

Table A8. Regression discontinuity effect of MPAs on fishing activity by proximity to ports using SAR data

	Vessels detection using SAR per 1000 km2			*Unseen vessel detection using SAR per millon km2*			*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)
Distance to Ports <334km									
Conventional	-68.00	-211.4***	-264.1***	-22.51***	-25.79***	-33.35***	0.06***	0.02***	0.06***
	(46.18)	(17.52)	(38.47)	(5.28)	(2.88)	(6.20)	(0.01)	(0.006)	(0.02)
Bias-corrected	-51.00	-209.9***	-277.4***	-21.2***	-22.59***	-34.5***	0.06***	0.04***	0.06***
	(46.18)	(17.52)	(38.47)	(5.28)	(2.88)	(6.20)	(0.01)	(0.006)	(0.02)
Robust	-51.00	-209.9***	-277.4***	-21.2***	-22.59***	-34.5***	0.06***	0.04***	0.06***
	(50.41)	(25.57)	(45.82)	(6.16)	(4.31)	(7.73)	(0.01)	(0.008)	(0.02)
Bandwidth (km)	6.33	50	18.38	15.62	50	17.35	8.74	50	13.11
Observations	91,423	496,802	85,949	91,423	496,802	85,949	91,423	496,802	85,949
Distance to Ports >334km									
Conventional	0.12	0.16**	0.28	-0.03	-0.07*	0.12	-0.002	-0.002	0.003
	(0.12)	(0.07)	(0.20)	(0.07)	(0.04)	(0.12)	(0.003)	(0.002)	(0.006)
Bias-corrected	0.1	0.16**	0.35*	-0.03	-0.06	0.16	-0.002	-0.003	0.005
	(0.12)	(0.07)	(0.20)	(0.07)	(0.04)	(0.12)	(0.003)	(0.002)	(0.006)
Robust	0.1	0.16	0.35	-0.03	-0.06	0.16	-0.002	-0.003	0.005
	(0.14)	(0.11)	(0.23)	(0.08)	(0.05)	(0.14)	(0.004)	(0.003)	(0.007)
Bandwidth (km)	11.59	50	11.89	13.71	50	10.77	13.75	50	11.19
Observations	37,771	415,067	36,252	37,771	415,067	36,252	37,771	415,067	36,252

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. The 334 km represents the median of the distribution of distance to the ports. 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. We present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

Table A9. Regression discontinuity effect of MPAs on fishing activity by MPA size using AIS data

	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)
			MPA Size <27,443 km2			
Conventional	39.71	-256.9	-1570.4***	65.58	-148.8***	-56.98
	(510.2)	(243.2)	(585.5)	(68.04)	(30.52)	(82.28)
Bias-corrected	149.3	19.63	-1759.7***	90.90	-29.95	-27.41
	(510.2)	(243.2)	(585.5)	(68.04)	(30.52)	(82.28)
Robust	149.3	19.63	-1759.7**	90.90	-29.95	-27.41
	(604.4)	(348.1)	(709.9)	(76.54)	(44.43)	(91.71)
Bandwidth (km)	10.38	50	11.39	8.79	50	12.75
Observations	49,423	357,180	45,858	49,423	357,180	45,858
			MPA Size >27,443 km2			
Conventional	-901.0***	-1620.2***	-672.9	-350.3***	-553.5***	-461.4***
	(296.8)	(163.5)	(520.3)	(80.38)	(36.33)	(110.6)
Bias-corrected	-774.5***	-974.2***	-452.5	-320.3***	-486.7***	-429.6***
	(296.8)	(163.5)	(520.3)	(80.38)	(36.33)	(110.6)
Robust	-774.5**	-974.2***	-452.5	-320.3***	-486.7***	-429.6***
	(349.3)	(243.5)	(598)	(91.97)	(53.09)	(131.6)
Bandwidth (km)	16.64	50	11.3	9.53	50	12.67
Observations	79,771	554,689	76,343	79,771	554,689	76,343

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. The 27,443 km2 represents the median of the distribution of MPA size. 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. We present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

Table A10. Regression discontinuity effect of MPAs on fishing activity by MPA size using SAR data

	Vessels detection using SAR per 1000 km2			*Unseen vessel detection using SAR per millon km2*			*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)
MPA Size <27,443 km2									
Conventional	-62.42	-47.15**	-159.7**	-38.16***	-30.67***	-52.02***	0.04***	0.02***	0.06
	(39.25)	(23.8)	(70.66)	(8.70)	(4.34)	(12.33)	(0.01)	(0.008)	(0.02)
Bias-corrected	-55.18	-33.04	-175.6**	-37.82***	-33.24***	-57.22***	0.05***	0.03***	0.07
	(39.25)	(23.8)	(70.66)	(8.70)	(4.34)	(12.33)	(0.01)	(0.008)	(0.02)
Robust	-55.18	-33.04	-175.6**	-37.82***	-33.24***	-57.22***	0.05***	0.03***	0.07
	(44.75)	(33.25)	(86.02)	(10.57)	(6.50)	(15)	(0.02)	(0.01)	(0.02)
Bandwidth (km)	14.97	50	14.06	13.52	50	13.29	9.85	50	12.04
Observations	49,423	357,180	45,858	49,423	357,180	45,858	49,423	357,180	45,858
MPA Size >27,443 km2									
Conventional	-128.9***	-295.5***	-262.9***	-17.59***	-28.17***	-27.14***	-0.09***	-0.11***	-0.1***
	(44.06)	(16.03)	(46.96)	(4.61)	(2.22)	(5.19)	(0.01)	(0.006)	(0.02)
Bias-corrected	-112.1**	-306.9***	-252.9***	-15.49***	-21.51***	-25.72***	-0.09***	-0.09***	-0.09***
	(44.06)	(16.03)	(46.96)	(4.61)	(2.22)	(5.19)	(0.01)	(0.006)	(0.02)
Robust	-112.1**	-306.9***	-252.9***	-15.49***	-21.51***	-25.72***	-0.09***	-0.09***	-0.09***
	(49.14)	(23.40)	(57.69)	(5.18)	(3.13)	(6.19)	(0.02)	(0.008)	(0.02)
Bandwidth (km)	5.98	50	12.53	8.23	50	16.15	9.87	50	12.83
Observations	79,771	554,689	76,343	79,771	554,689	76,343	79,771	554,689	76,343

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. The 27,443 km2 represents the median of the distribution of MPA size. 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. We present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

Table A11. Regression discontinuity effect of MPAs on fishing activity by fishing conditions

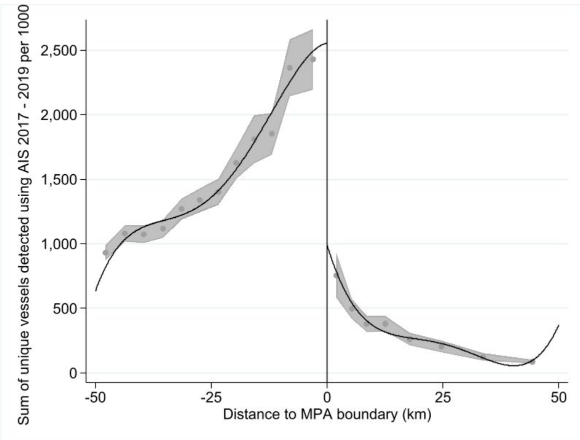
	Fishing Hours per 1000 km2	*Vessels detection using AIS per 1000 km2*	*Vessels detection using SAR per 1000 km2*	*Unseen vessel detection using SAR per 1000 km2*	*Pr(Unseen vessel detection using SAR)*
	(1)	(2)	(3)	(4)	(5)
			No Good Fishing Condition		
Conventional	-1032.2***	-378.2***	-193.9***	-24.96***	-0.02***
	(137.9)	(24.75)	(13.63)	(2.16)	(0.005)
Bias-corrected	-520.2***	-301.1***	-191.5***	-21.25***	0.004
	(137.9)	(24.75)	(13.63)	(2.16)	(0.005)
Robust	-520.2**	-301.1***	-191.5***	-21.25***	0.004
	(210.6)	(36.63)	(20.51)	(3.31)	(0.007)
Bandwidth (km)	50	50	50	50	50
Observations	879,680	879,680	879,680	879,680	879,680
			Fishing Condition yr=1		
Conventional	-106.7	-3.55	-105.4***	-91.25***	-0.03
	(66.63)	(8.49)	(37.79)	(21.71)	(0.04)
Bias-corrected	-190.5***	-2.35	-101.8***	-92.07***	-0.04
	(66.63)	(8.49)	(37.79)	(21.71)	(0.04)
Robust	-190.5	-2.35	-101.8***	-92.07***	-0.04
	(117.2)	(12.12)	(35.88)	(30.57)	(0.05)
Bandwidth (km)	50	50	50	50	50
Observations	28,287	28,287	28,287	28,287	28,287
			Fishing Condition yr>=2		
Conventional	240.9	-17.67	54.72	-75.77	0.05
	(178.9)	(22.77)	(74.38)	(62.29)	(0.09)
Bias-corrected	191.6	-22.75	84.41	-18.58	0.08
	(178.9)	(22.77)	(74.38)	(62.29)	(0.09)
Robust	191.6	-22.75	84.41	-18.58	0.08
	(196.8)	(30.31)	(90.08)	(88.43)	(0.13)
Bandwidth (km)	50	50	50	50	50
Observations	3,902	3,902	3,902	3,902	3,902

Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. The fishing condition variable is expressed as the number of years that the grid has had good fishing conditions according to the formula proposed by Axbard (2016). Calonico et al. (2014) RD estimate used with fixed 50 kms bandwidth. All regressions control for the climatic, physical and biological variables. We present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.

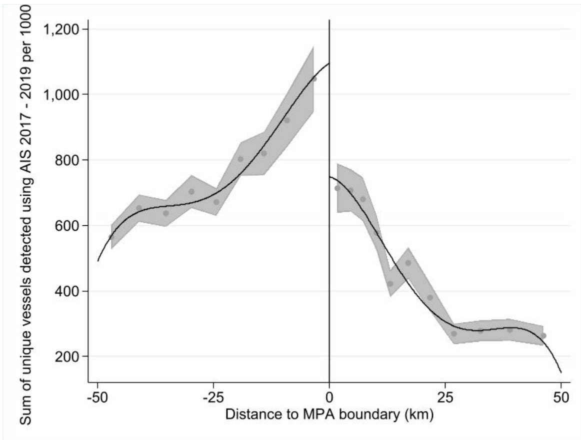
Table A12. Regression discontinuity effect of MPAs on fishing activity by proximity to piracy events

	Fishing Hours per 1000 km2	*Vessels detection using AIS per 1000 km2*	*Vessels detection using SAR per 1000 km2*	*Unseen vessel detection using SAR per 1000 km2*	*Pr(Unseen vessel detection using SAR)*
	(1)	(2)	(3)	(4)	(5)
			Piracy Event <5km		
Conventional	-1968.7	411.1	-2310.8**	-66.65	0.07
	(5576)	(416)	(1158.5)	(209.9)	(0.13)
Bias-corrected	-3716.7	457	-2264.7*	33.17	-0.002
	(5576)	(416)	(1158.5)	(209.9)	(0.13)
Robust	-3716.7	457	-2264.7	33.17	-0.002
	(8113)	(563.7)	(1575.8)	(330.5)	(0.2)
Bandwidth (km)	50	50	50	50	50
Observations	1,247	1,247	1,247	1,247	1,247
			Piracy Event >5km		
Conventional	-1007***	-368.3***	-187.9***	-25.83***	-0.02***
	(133.2)	(23.95)	(13.08)	(2.18)	(0.005)
Bias-corrected	-517.1***	-294.4***	-186.1***	-22.15***	0.004
	(133.2)	(23.95)	(13.08)	(2.18)	(0.005)
Robust	-517.1**	-294.4***	-186.1***	-22.15***	0.004
	(203.1)	(35.47)	(19.64)	(3.32)	(0.007)
Bandwidth (km)	50	50	50	50	50
Observations	910,622	910,622	910,622	910,622	910,622

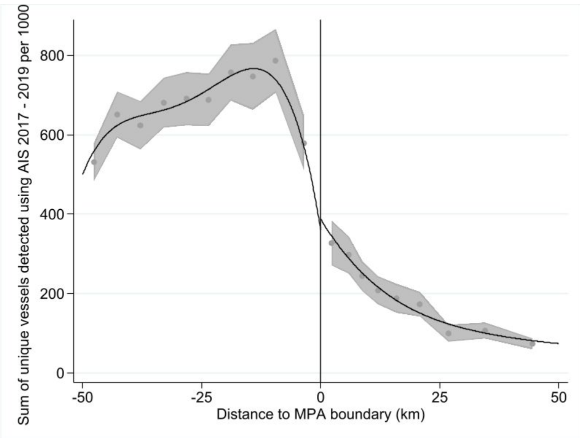
Source: Authors' calculations based on data from GFW, ProtectedSeas, Anti-shipping Activity Messages (ASAM) database and MODIS. Note: * is significant at 10%, ** at 5%, and *** at 1% level. Calonico et al. (2014) RD estimate used with fixed 50 kms bandwidth. All regressions control for the climatic, physical and biological variables. We present the results based on a first order local-polynomial. Standard errors in parentheses are based on a nearest neighbor variance estimator.



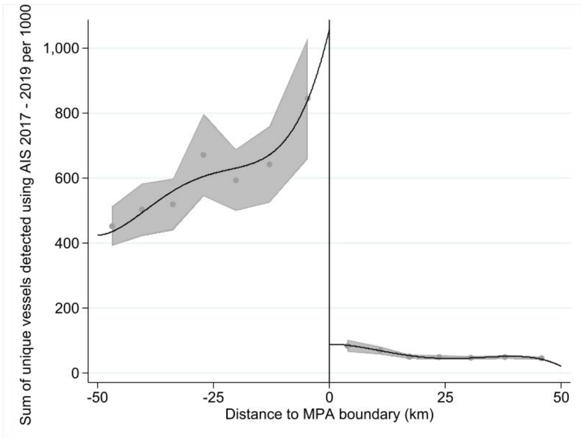
***(a)** Least restrictive*



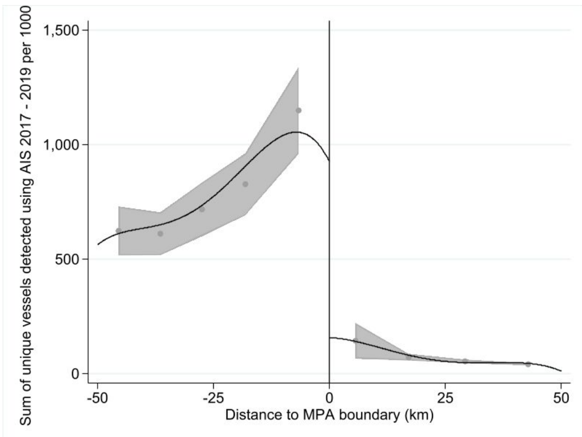
***(b)** Less restrictive*



***(c)** Moderately restrictive*

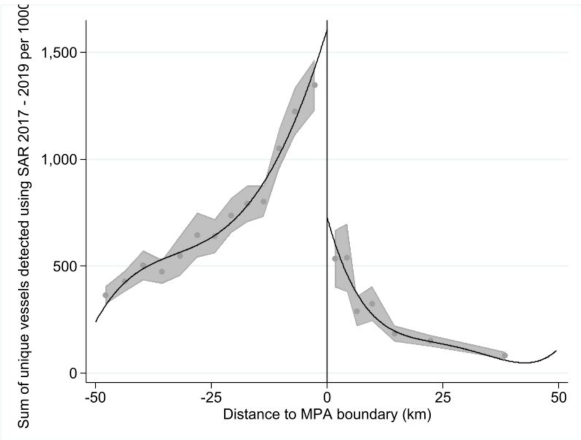


***(d)** Heavily restrictive*

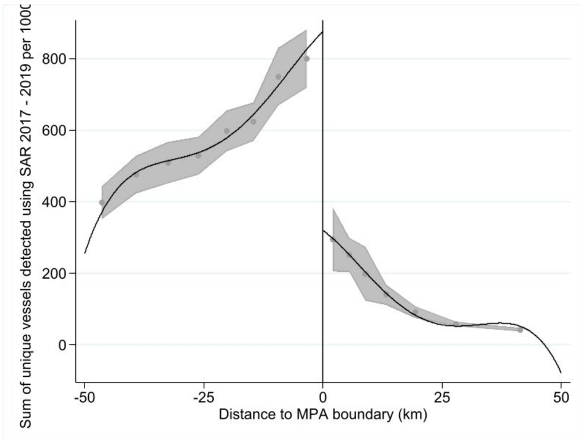


***(e)** Most restrictive*

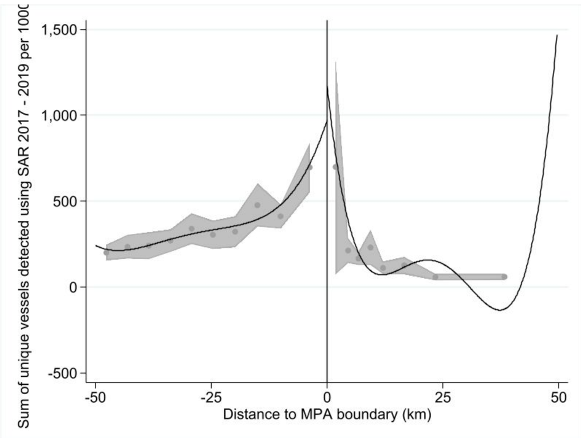
Figure A2. Regression discontinuity effect of MPAs on vessel detections using AIS data by levels of protection. Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: The left side of the figure shows the observations outside the MPAs, and the right side shows the observations inside the MPAs. The observations are binned according to the data-driven procedure IMSE-optimal quantile-spaced method using polynomial regression. The gray shading represents the confidence intervals at the 95% confidence level. All graphs present the estimates following the donut hole approach with a 2km exclusion zone.



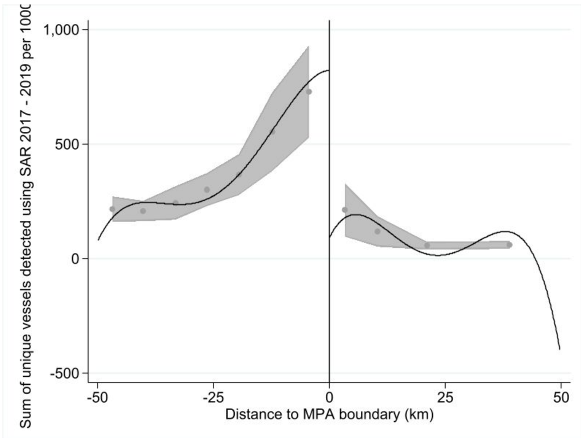
***(a)** Least restrictive*



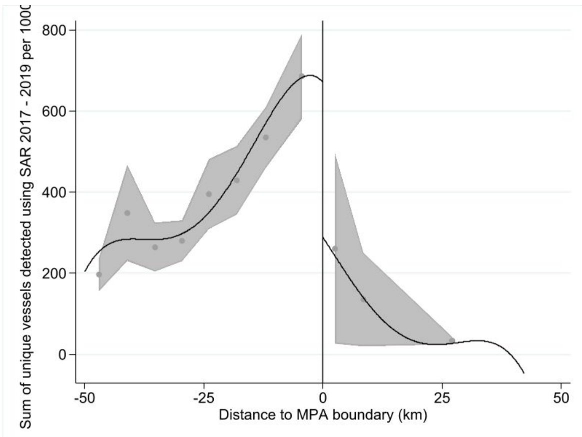
***(b)** Less restrictive*



***(c)** Moderately restrictive*

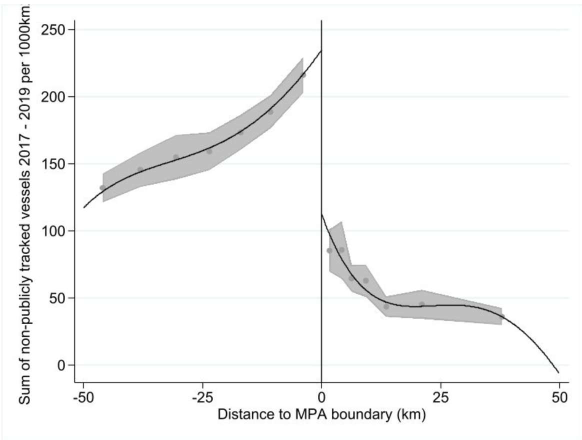


***(d)** Heavily restrictive*

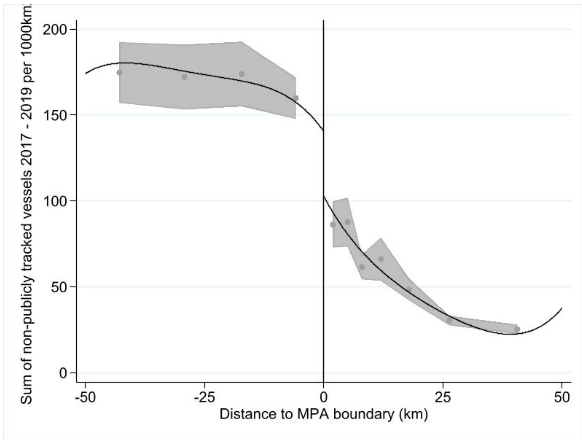


***(e)** Most restrictive*

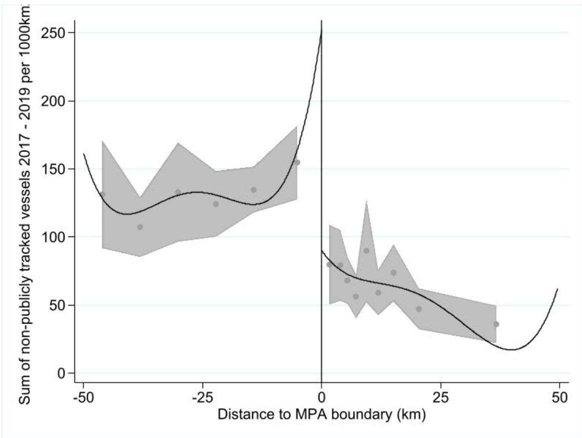
Figure A3. Regression discontinuity effect of MPAs on vessel detections using SAR data by levels of protection.Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: The left side of the figure shows the observations outside the MPAs, and the right side shows the observations inside the MPAs. The observations are binned according to the data-driven procedure IMSE-optimal quantile-spaced method using polynomial regression. The gray shading represents the confidence intervals at the 95% confidence level. All graphs present the estimates following the donut hole approach with a 2km exclusion zone.



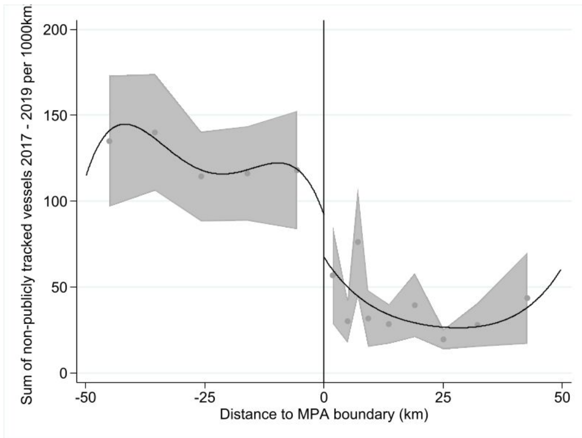
(a) *Least restrictive*



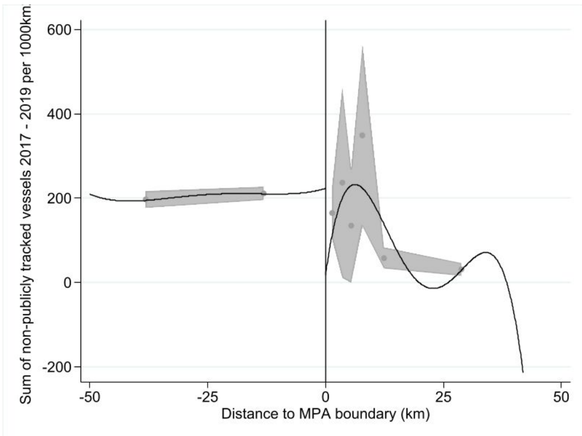
(b) *Less restrictive*



(c) *Moderately restrictive*

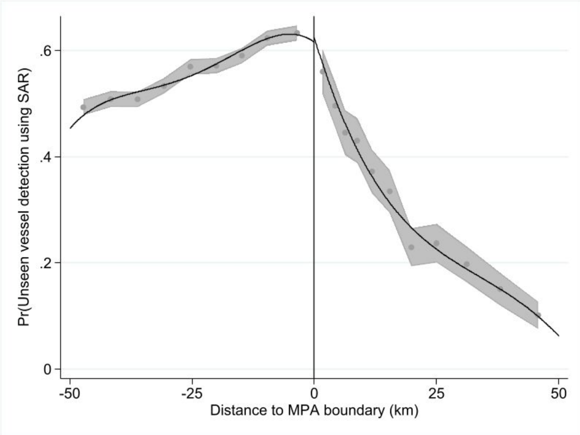


(d) *Heavily restrictive*

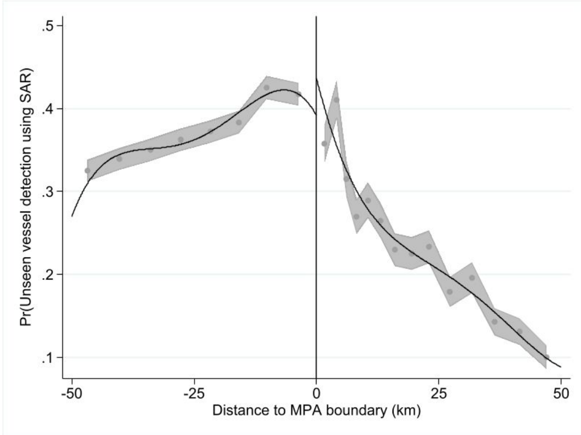


(e) *Most restrictive*

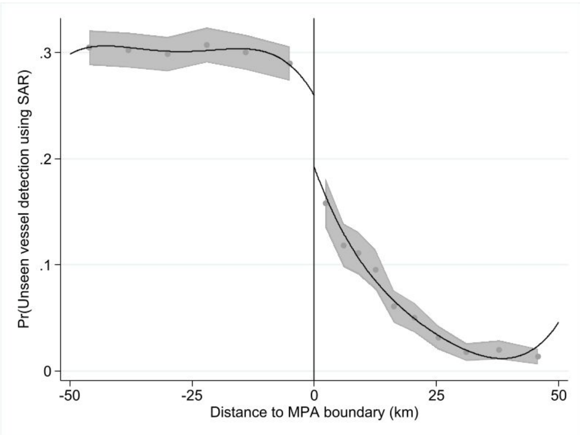
Figure A4. Regression discontinuity effect of MPAs on vessel detctions no-publicly tracked by levels of protection. Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: The left side of the figure shows the observations outside the MPAs, and the right side shows the observations inside the MPAs. The observations are binned according to the data-driven procedure IMSE-optimal quantile-spaced method using polynomial regression. The gray shading represents the confidence intervals at the 95% confidence level. All graphs present the estimates following the donut hole approach with a 2km exclusion zone.



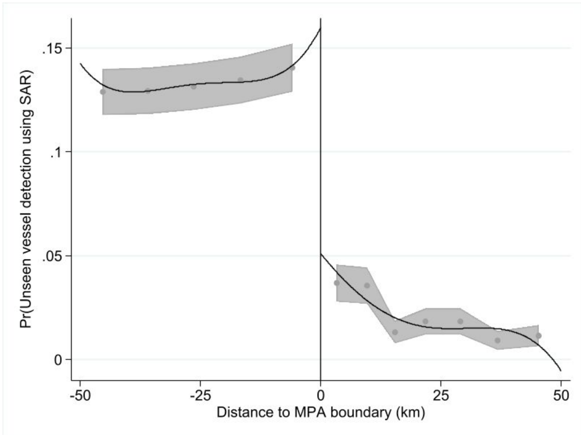
***(a)** Least restrictive*



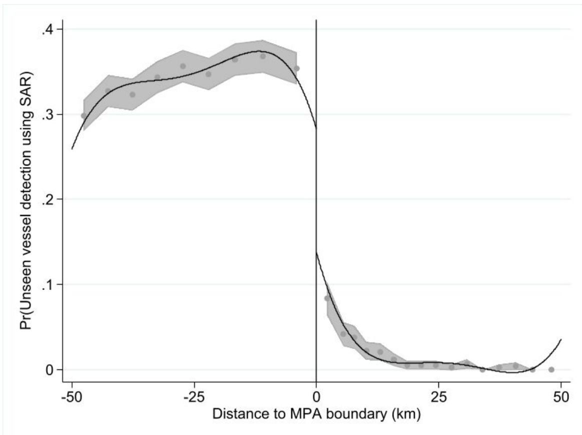
***(b)** Less restrictive*



***(c)** Moderately restrictive*

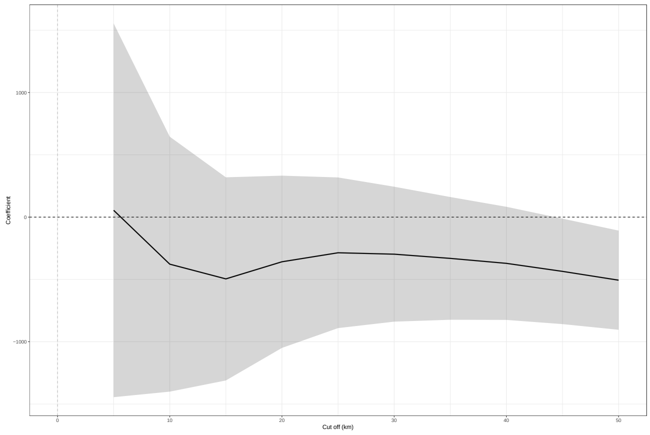


***(d)** Heavily restrictive*

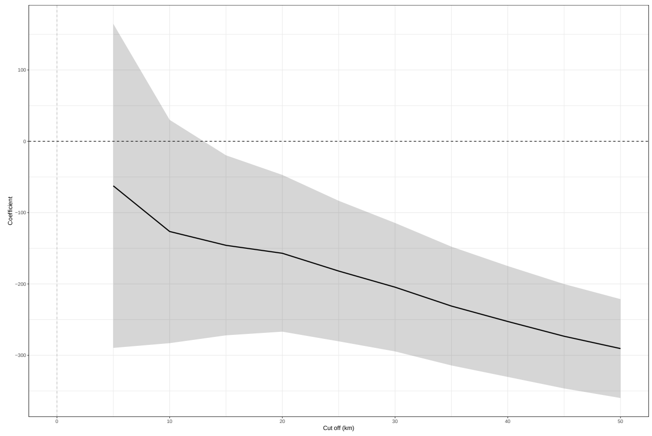


***(e)** Most restrictive*

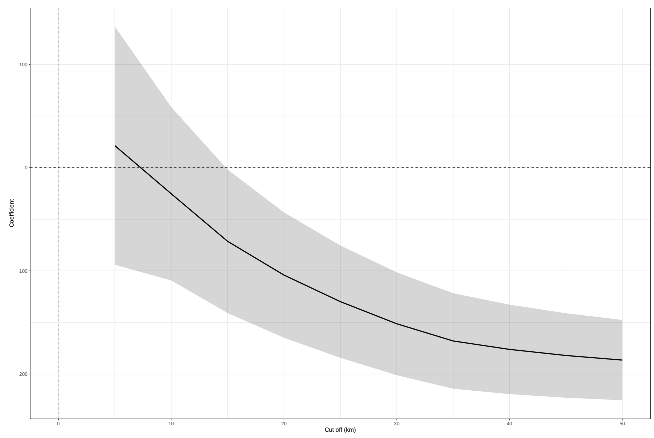
Figure A5. Regression discontinuity effect of MPAs on probability of vessel detections no-publicly tracked by levels of protection. Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: The left side of the figure shows the observations outside the MPAs, and the right side shows the observations inside the MPAs. The observations are binned according to the data-driven procedure IMSE-optimal quantile-spaced method using polynomial regression. The gray shading represents the confidence intervals at the 95% confidence level. All graphs present the estimates following the donut hole approach with a 2km exclusion zone.



(a) *Fishing hours*

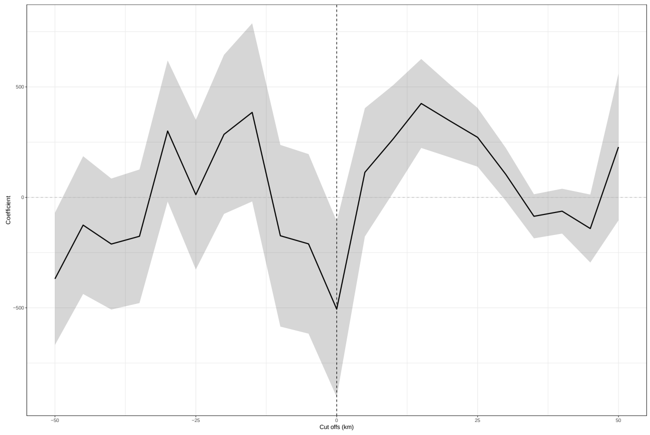


(b) *Vessels detected using AIS*

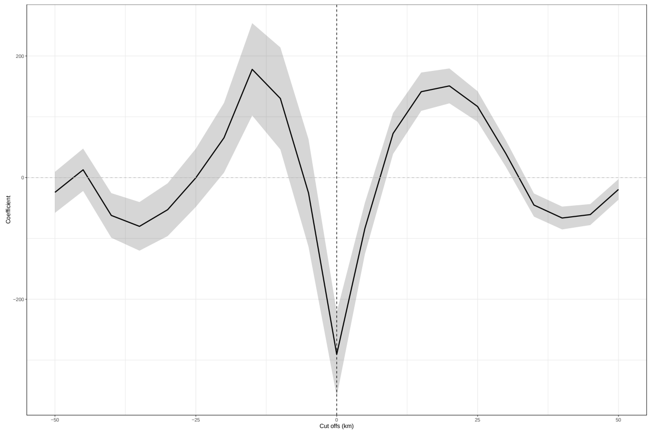


(c) *Vessels detected using SAR*

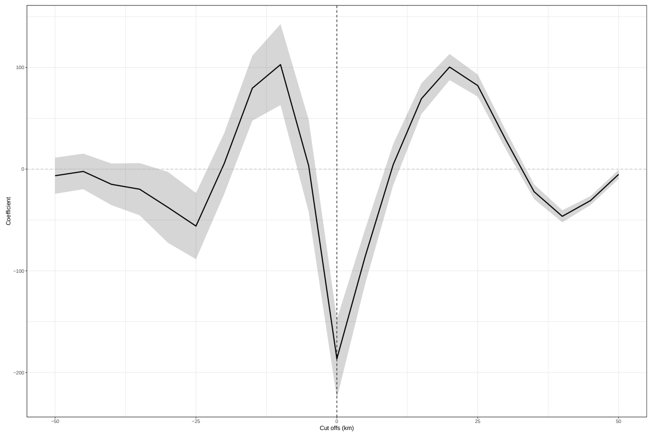
Figure A6. Bandwidth Sensitivity. Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: Each graph presents the estimates based on the Calonico et al. (2014) RD estimators with a fixed bandwidth ranging from 5 to 50 km in increments of 5 km. All regressions control for the climatic, physical and biological variables. We present the results based on a first order local-polynomial. Standard errors are based on a nearest neighbor variance estimator.



(a) *Fishing hours*



(b) *Vessels detected using AIS*



(c) *Vessels detected using SAR*

Figure A7. Placebo threshold test for RD effects. Source: Authors' calculations based on data from GFW, ProtectedSeas and MODIS. Note: Each graph presents the estimates with a placebo for the boundary moving along 50 km on both sides of the MPA borders, with an increment of 5 km, based on the Calonico et al. (2014) RD estimators with a fixed bandwidth of 50 km. All regressions control for the climatic, physical and biological variables. We present the results based on a first order local-polynomial. Standard errors are based on a nearest neighbor variance estimator.