OCEANOGRAPHY

# The largest fully protected marine area in North America does not harm industrial fishing

**Fabio Favoretto[1,2]*, Catalina López-Ságastegui[3], Enric Sala[4], Octavio Aburto-Oropeza[2]**



**Marine protected areas (MPAs) that ban fishing restore marine life within their boundaries and can also replenish nearby fisheries. However, some argue that after large MPAs are established, fishing effort is displaced to unprotected areas and economic loss is incurred by the fishing industry. We tested these assumptions by assessing the behavior and productivity of the Mexican industrial fishing fleet before and after the implementation of the largest fully protected MPA in North America (the 147,000–square kilometer Revillagigedo National Park). We found no decrease in catches and no causal link between the variation of the spatial footprint of the industrial fleet and the implementation of the MPA. Our findings add to growing evidence that well-designed MPAs benefit marine ecosystems and, in the long term, can also benefit the fisheries they support.**

## INTRODUCTION

Marine protected areas (MPAs) where fishing is prohibited benefit ocean biodiversity, help improve nearby fisheries, and mitigate climate change (*1*–*3*). However, despite scientific recommendations and international commitments to protect at least 30% of the ocean, less than 3% of the global ocean is highly or fully protected [as defined in the MPA Guide (*4*) as of October 2022 (*5*)]. A major reason for this gap is the strong opposition from the fishing industry, which sees fishing bans as a threat to their business and livelihoods. Critics argue that highly protected MPAs cause catch loss and displace efforts elsewhere, potentially ending with a net impact on biodiversity and fisheries (*6*–*9*). These claims are often conflated into broader narratives (*6*, *10*), where negative outputs are argued without acknowledging a highly capitalized fishing industry with a large adaptive capacity (*11*). If MPAs are to contribute to more sustainable and equitable use of the oceans, then specific discussions must be informed by evidence. Here, we present a before/after analysis to understand the effect of establishing a large, fully protected MPA, on catches and the spatial footprint of industrial fisheries.

In November 2017, the Revillagigedo National Park (henceforth, "the MPA") was established in the Mexican Pacific, becoming the 13th largest MPA in the world and encompassing 4.2% of Mexico's exclusive economic zone (EEZ). The National Park is fully protected from fishing and other extractive activities. Although the Mexican government claims that MPAs cover 21.8% of Mexico's EEZ, only Revillagigedo and a few small MPAs (totaling 4.6% of the EEZ) are fully protected, leaving 95.4% of the EEZ open to fishing. The Mexican fishing sector was particularly vocal against the establishment of the MPA, claiming a potential loss of up to 20% of their tuna and pelagic catches (*12*).

In this study, 5 years after the MPA's implementation, we can empirically test the following questions: (i) Did the MPA successfully reduce fishing effort within its boundaries? (ii) Did fishing catches on aggregate decrease after the MPA's implementation? (iii) Did the MPA cause a significant change in the spatial footprint of the fishing fleet? To answer these questions, we use vessel monitoring system (VMS) data from the Mexican fishery commission, official fisheries landings data, and causal impact models with counterfactual scenarios of before/after effects. Specifically, we focus on the 212 vessels with fishing permits for pelagic fish (tuna, sharks, and swordfish, using longlines and purse seine gears).

We use a causal impact model to estimate the causal effect of a designed intervention on a time series (*13*). In addition, we used a model framework using mixed models with a before-after causal impact design (see the Supplementary Materials). While the results were like the causal impact approach, the latter is better suited for cases when a randomized experiment is not available. Given a response time series, the causal impact model constructs a Bayesian structural time series that predicts a counterfactual scenario that would have evolved if the MPA had never been established. Here, we assess fishing effort (fishing hours per number of vessels), catch per unit of effort (CPUE; in metric tons per day), and the area (square kilometers) used by each vessel from 2008 to 2022. These variables combined describe the overall behavior of the fleet to answer our three questions.

## RESULTS

### Did the MPA successfully reduce fishing effort within its boundaries?

Yes, fishing activity within the MPA declined on average by 82% [95% confidence interval (CI): −141%, −31%] ($P = 0.005$) from before to after implementation (from 18.85 hours per vessel to 3.37 hours per vessel) (Fig. 1A and fig. S3). Fishing activity occurring within the MPA after its implementation is illegal; vessels detected within the MPA did not just cross its boundaries but performed maneuvers that can be associated with fishing gear deployment.

[1]Centro para la Biodiversidad Marina y la Conservación, A.C., Calle del Pirata 420, Col. El Mezquite, La Paz, BCS, México. [2]Scripps Institution of Oceanography, University of California San Diego, 9500 Gilman Drive, La Jolla, CA 92093, USA. [3]Gulf of California Marine Program, Institute of Americas, UC San Diego Campus, 10111 North Torrey Pines Road, La Jolla, CA 92037, USA. [4]National Geographic Society, Washington, DC 20036, USA.
*Corresponding author. Email: ffavoretto@ucsd.edu

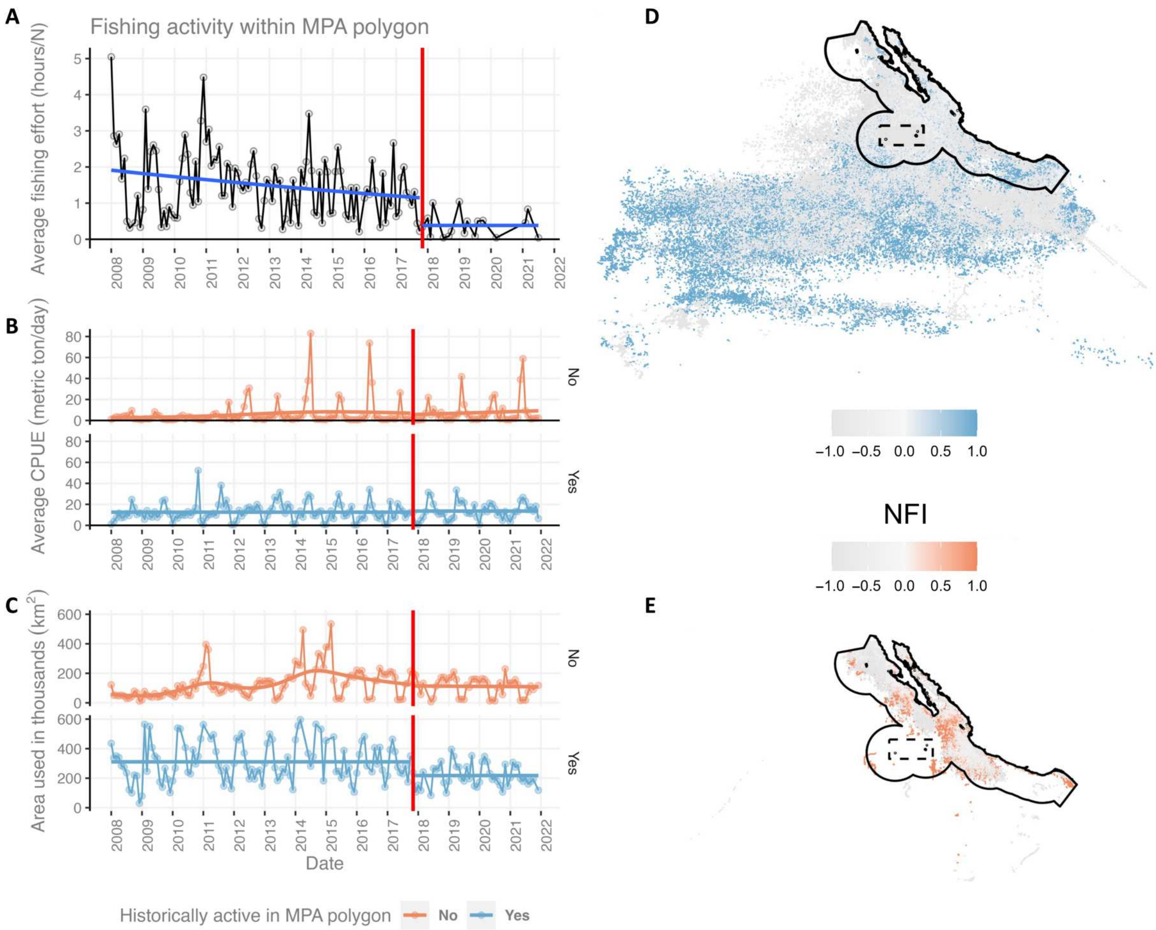


**Fig. 1. Variables describing the overall behavior of the fleet to test our three questions.** (A) Average monthly fishing effort (fishing hours per vessel) observed within the MPA polygon. (B) Average monthly catch per unit of effort (CPUE; in metric tons per day) for vessels historically active inside the MPA polygon (blue circles) and those who never fished in the area (orange circles). (C) Average area used by the vessels monthly. The red vertical line marks the MPA's implementation date. The trend lines are generalized additive models fitted with a Gamma family distribution and are fitted for descriptive purposes. Trend lines resulting from the causal impact modeling are available in the Supplementary Materials. Maps of the normalized fishing index (NFI) (at 0.1° pixel resolution) for (D) the fleet historically active within the MPA polygon and (E) the fleet that was never active inside the MPA polygon. NFI considers the difference in fishing effort (hours per vessel) within each pixel before (2014 to 2017) and after (2018 to 2021) the MPA's implementation. The difference in effort was normalized between −1 and 1, representing a decrease and an increase in fishing effort, respectively. In the maps, the black line represents Mexican EEZ, and the dashed rectangle is the MPA polygon.

### Did fishing catches decrease after the MPA's implementation?

No, we found no statistical evidence of a significant, negative, causal impact of the MPA's implementation on industrial fisheries in Mexico's Pacific EEZ. The average CPUE of the vessels that were historically active in the MPA polygon (Fig. 1B) did not change significantly ($P = 0.43$) after implementation (fig. S4) nor did the CPUE of those who were never active within the MPA ($P = 0.15$; Fig. 1B).

### Did the implementation of the MPA result in an increase of the fishing fleet's area use?

No, our results show that the total ocean area used by industrial fishing vessels in the Mexican Pacific decreased significantly. After November 2017, the area used by vessels that historically fished within the MPA (Fig. 1C) decreased significantly ($P = 0.003$) an average 53% (95% CI: −88%, −20%) (fig. S6), while the total ocean area used by vessels that never used the MPA for fishing (Fig. 1C) decreased an average of 55% (95% CI: −74%, −36%) ($P = 0.001$) (fig. S7). The total area used by the fishing fleet from 2014 to 2021 (4 years before and 4 years after the MPA's implementation) was 6,289,643 km$^2$, of which the Park's area represents ~2.3% (147,000 km$^2$). Furthermore, the normalized fishing index (NFI) showed that effort decreased in more area (42 and 44% for vessels that historically used the MPA and the ones who did not, respectively; Fig. 1, D and E) than it increased (18.8 and 26% for vessels that historically used the MPA and the ones who did not, respectively; Fig. 1, D and E). Notably, the fleet that was historically active within the MPA (Fig. 1D) conducted most of their fishing in the high seas before and after the MPA's implementation.

## DISCUSSION

Implementing the 147,000-km$^2$ Revillagigedo National Park had no negative effect on catches (Fig. 1B) or caused Mexico's industrial fleet to increase the area used for fishing (Fig. 1C). These findings refute the fishing industry's argument that creating the Revillagigedo MPA would harm the fishery or directly cause the effort to move, thus increasing the fishing area. Similar results were recorded in other Pacific MPAs but with less reliable data or in MPAs where fishing effort was already low (*14*–*17*).

In Revillagigedo, fishing effort was successfully reduced within its boundaries, thus protecting a critical ecosystem (*18*) that the fishing industry could have continuously targeted. Using satellite tracking technology, we found only a few isolated cases of potential illegal fishing within the MPA after its establishment in late 2017 (Fig. 1A). This is due, in part, to compliance from the fishing industry and to the MPA managers' efforts to use an automatic identification system (AIS) monitoring system (Skylight) to help monitor the protected area. These results contribute to the growing evidence showing how large pelagic MPAs can be enforced using technology and can become conservation assets if well managed (*11*) and fully protected (*4*).

Fishing fleet behavior is affected by numerous factors, ranging from environmental to political and economic ones, including fisheries regulations (*19*–*21*). Fishing effort or displacement (e.g., toward high seas; Fig. 1D) can change because of social and political agendas (*21*), which aim to provide fishers with the means to increase their fishing effort, with limited revenue benefits (*22*, *23*).

In the Mexican Pacific, the variation in the spatial footprint of the fishing fleet may be determined by changes in oceanographic conditions and the effects of climate change that are causing a redistribution of fisheries catch at a global scale (*19*). The Mexican Pacific has some of the highest rates of catch tropicalization worldwide (*24*), which might cause a catch increase in some species but a net loss in fishery yields (*25*). Specifically, tropical tuna species are projected to be more abundant and might be what the vessels in Mexico are targeting when fishing near the tropics (Fig. 1D).

The expansion of fishing grounds toward the high seas was driven by technological advancements (*26*) and is sustained by economic mechanisms like fishery subsidies (*22*). The growth of the fishing footprint in Mexico (Fig. 1D) resembles a pattern of discovery and depletion of fishing grounds (*26*), which attempts to maintain catches by moving to more profitable areas. However, catches reported by vessels that used to fish in Revillagigedo, which showed a larger spatial footprint (Fig. 1D), did not increase over time (Fig. 1B) despite the increased effort in tropical fishing grounds. A possible explanation is that these areas are already intensively exploited (*21*, *22*, *26*) or beginning to show signs of the decreases in yields predicted by climate change scenarios (*19*, *24*, *27*–*31*).

Now, spatially explicit data on fisheries catches have not been made available by the Mexican fisheries commission; therefore, it is difficult to determine whether spillover effects are occurring around the MPA (*3*). We hope that the Mexican fisheries commission can soon recognize that data transparency and quality assessments can improve scientific analysis for responsible decision-making. Openly available geolocalized catch reports (*32*) could help improve fisheries management beyond Mexico and the Mexican Pacific now that remote monitoring and analysis tools are available (e.g., Skylight and Global Fishing Watch). In remote areas where monitoring and surveillance are difficult, technologies such as AIS and VMS have proven to be effective tools in combating illegal fishing [e.g., (*14*, *15*)]. These systems enable authorities to track the movements of fishing vessels and identify any suspicious activity, ultimately deterring illegal fishing and ensuring that fishermen adhere to regulations. Data transparency and availability not only can improve fisheries management, assessments, and spatial planning of human activities but also are assets that enable auditing and counteracting claims of illegal activities that can harm the fishing industry more significantly than MPAs [e.g., international reports that may lead to export bans (*33*)].

Even if large, oceanic, fully protected MPAs reduce fishing effort without negatively affecting the fishing industry, they are not the only solution to ocean conservation. Industrial fishing vessels have the flexibility and potential to readily change their fishing grounds, which might be more challenging for artisanal fisheries, which tend to be limited in terms of their operating grounds. MPAs must be properly contextualized and complement other management measures, regulations, controls, and restrictions (*34*, *35*). Our work shows that it is possible to find common ground between area-based conservation and extractive activities like fishing and to foster cooperation between different sectors to achieve the global 30 × 30 target.

## MATERIALS AND METHODS

The process of downloading and wrangling data, the datasets' structure, and a schematic view of the analysis workflow is explained in detail in our GitHub repository documentation: https://github.com/CBMC-GCMP/mpas_do_not_harm_fishery. We coded all this preprocessing and follow-up analysis with the R programming language using the RStudio integrated development environment (*36*). For convenience, we created an R package "dafishr" that is available for free download in the GitHub page that contains all the dependencies and functions needed (*37*). Here, we provide a description of the processing stages (fig. S1).

### Datasets used

Preprocessed and wrangled datasets used for the analysis are available through our repository in Zenodo (*38*), GitHub, and R package (*37*). Raw version of the files can be downloaded using our code (*37*, *38*) or through the official web page (*39*).

We downloaded VMS data from the National Commission for Fisheries and Aquaculture (CONAPESCA) official web page (*39*). The VMS data consist of satellite geo-positioning pings with a 1-hour interval, transmitted by each vessel from 2008 to 2021. The VMS dataset reports vessel's name, unique ID, speed, and navigation bearing. After cleaning and standardization, the dataset has ~150 million data rows, representing tracks of 2287 industrial vessels.

We requested the landing dataset from CONAPESCA by a formal request with data from 2008 to 2021. Detailed information on the dataset version used for this analysis can be found in our GitHub repository, where it can be downloaded through R. The raw datasets are available at this Dryad repository (*38*).

We used the MPA polygons from the National Commission for Natural Protected Areas (CONANP) that is available as a shapefile at http://sig.conanp.gob.mx/website/pagsig/info_shape.htm. We also provide a working version of the shapefile within the dafishr package datasets. We used the point locations of ports, marinas, and landing areas for industrial vessels available at the National Institute of Statistics and Geography.

We obtained the fishing gear permits datasets from CONAPESCA by a formal request, and the data are available for reproducibility purposes in the dafishr package. A full version is available through authors under request.

### Data cleaning and formatting

Raw data can be downloaded by year and are organized in several tabular files representing monthly or biweekly intervals. Then, the preprocessing code finds and eventually filters out, if needed, corrupted latitude, longitude, or speed entries that have obvious erroneous values; and then, it formats dates and label corrupted rows. In the files, the information stored is sometimes inconsistent, and there are some errors within the rows, for example, some corrupted dates or vessel codes. The most evident case came from the RLMSEP_2020/10.-OCTUBRE/16-31 OCT 2020.csv file that had all dates corrupted, and we filtered it out from our analyses.

### Spatial cleaning and labeling

After the cleaning step, the preprocessing code performs a spatial intersection with a vector file representing land to further eliminating dubious points falling inland and, after that, creates a buffer of 0.025° (~2.6 km) around ports to spatially label all vessel activity within port and exclude them from potential fishing activity modeling. The preprocessing then intersects all the coordinates with a polygon representing the Pacific portion of the Mexican EEZ and all the MPA polygons in Mexico. Then, we labeled vessels that were found fishing in Revillagigedo MPA polygon and those who were never found fishing in the area. We defined these vessels as "historically fished in Revillagigedo" versus the one that "never fished in Revillagigedo area."

### Data checks

After all the cleaning steps, a global check of dates is made to be sure that all data are in the correct units and that no vessels have inaccurate hours of activities assigned to them (e.g., more than 24 hours in a day). Through this step, we realized that some tracks are reported in minutes; thus, we homogenized all data by hours, and, for those points reported in minutes, we averaged the latitude and longitude coordinates.

### Fishing activity modeling

VMS data can be modeled on the basis of speed to infer potential fishing activities from vessel tracks and understand vessel behavior. For example, whether a vessel was cruising or if it was slowing down to deploy fishing gear. Not all the methods used to model fishing behavior are easily reproducible on a personal computer or are open source (*21*, *40*–*43*). We used a trip-based Gaussian mixture model, which has a lower maximum error rate per trip, low false-positive rates, and good performance in terms of computing efficiency when applied to VMS data (*42*). These characteristics allow an accurate estimation of the spatial distribution of active fishing while also being computationally efficient. We fitted the Gaussian mixture models using an expectation-maximization algorithm (*43*) to estimate the parameters of the multimodal speed distribution using the mixtools R package (*44*). We assumed three univariate normal distributions corresponding to three states of a vessel: fishing, deploying gear, and steaming. The starting values for the mean and SD for each underlying distribution were estimated visually using a histogram showing the multimodal distribution of speed (fig. S2). We then defined the upper limit to the distribution for the fishing state by estimating the mean and adding two SDs to it. The model labels all positional records with speeds exceeding the upper limit as "not fishing" (encompassing deployment and steaming). Such labeling also grants a degree of conservatism to our model because deployment and steaming speeds sometimes overlap.

### Fishing effort and catch data

We used only vessels that had permits for purse seine and longlines fishing gears targeting tuna, shark, and swordfish species. We then constructed the time series of fishing effort within the Revillagigedo MPA polygon by dividing the modeled fishing hours by the number of vessels detected each month from 2008 to 2022. Then, we calculated the CPUEs by using the landing datasets. For each of the selected vessels, we extracted fishing days declared at port as well as their catches. We calculated the CPUE as catch in metric ton divided by the days at sea each month. We then averaged the CPUE for all the vessels of the ones that historically fished in the Revillagigedo polygon and the ones who never did.

### Area used calculation

We used only vessels that had permits for purse seine and longlines fishing gears targeting tuna, shark, and swordfish species. We used the coordinates of the modeled fishing activities for the vessels who historically fished in Revillagigedo, and the ones who never did, to create rasters of 0.1° × 0.1°, where each pixel contains the total fishing hours divided by the number of unique active vessels enclosed in that area each month.

### Area displaced

We calculated the total area of the raster for each month. Last, we created rasters of the total fishing area from 4 years before (2014 to 2017) and 4 years after (2018 to 2021) the Park implementation. Then, to calculate displacement in terms of space (i.e., fishing footprint), we used the rasters before and the rasters after Park implementation and computed a NFI to compare them (Eq. 1). The index returns values from −1 to 1 when fishing activity decreases or increases, respectively

$$\text{Normalized fishing index} = \frac{\sum \text{Raster after} - \sum \text{Raster before}}{\sum \text{Raster after} + \sum \text{Raster before}} \tag{1}$$

### Before/after modeling

To test the effect of MPA establishment fishing effort (fishing hours per number of active vessels), CPUE (catches in metric tons per day at sea), and area used, we used a causal impact model by applying a Bayesian structural time series method (*13*). The model predicts a counterfactual scenario for the response variable (e.g., the fishing activity or catch) as if the establishment of the MPA had never occurred. First, we defined the pre-establishment and post-establishment periods by using the date of Revillagigedo MPA implementation (November 2017) as a threshold. During the pre-establishment period, the model fits the pattern of the observed variation in the response variable and then predicts the trend in the post-establishment period of data creating the counterfactual scenario. The effect of the implementation is quantified by comparing the expected trend of the counterfactual model against the observed trend of the response variable. Because fishing data had a seasonality component, we accounted this into the model by specifying a monthly granularity. The modeling was done using the CausalImpact package (*13*).

### Methods′ limitations

Our methods used have some limitations that are important to disclose so that results can be interpreted correctly. First, we provide a "fishing hours" variable that represents a potential fishing activity that is modeled according to fishing speed. There is no certainty that the vessel caught fish at the locations labeled by the model. Nevertheless, our estimates are made in such a way that are conservative and do represent an effort to find and catch fish. In the calculations for the fishing area, we arbitrarily decided to have a 0.1° resolution to create the raster. Such a resolution can overestimate the area used by the fishing fleet by some degree; however, for the purpose of our manuscript, such estimate error is far less than the displacement that we would have expected from the Revillagigedo MPA establishment. Furthermore, even at different resolutions, we would have similar results as our goal was not to precisely measure an area but to calculate its relative difference in time. We therefore consider that, within the study goal, a different resolution is not twisting the interpretation of the results nor the message that we want to convey.

## Supplementary Materials

**This PDF file includes:**
Supplementary Text
Figs. S1 to S8

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