

What is the economic impact of Large-Scale MPAs in the Pacific Ocean?

Authors: John Lynham; Anton Nikolaev; Thais Vilela

Comments by Juan Carlos Villaseñor-Derbez

2018-07-26

Contents

Possible contributions	1
US Pacific Monuments	1
Total revenue	1
Total costs (TC)	1
TC from NOAA Observer program	2
TC from GFW Data	2
PIPA and Palau	3
Further work	8
Other details	8
References	10

Possible contributions

As I understand the efforts made so far, there are two straightforward ways in which I could contribute to this study. For the first one I would help strengthen the analysis of NOAA Observer and GFW data for the US PNMs. The second one would involve conducting the analysis of GFW data for PIPA, and translating the results into implications for Palau. I discuss these two in greater detail in the next paragraphs.

US Pacific Monuments

In this section I include possible analysis in which I could help. When relevant, I include quotes to provide context. Comments are organized with headings similar to the ones included in the original manuscript. I believe my suggestions would compliment (rather than replace) current analysis, and I acknowledged that you might have already tried some or that due to data constraints not all of them are possible.

Total revenue

“It is very clear from the figure that total catch of bigeye has not declined as a result of the 2014 or 2016 expansions”. Of course, I have not reviewed the data. But is it safe to conclude this? At least through time there isn’t an evident decrease, but what would have catches looked like had PMNM not been expanded?

Not sure if the spatial resolution (*i.e.* Catch Blocks) in logbooks allows this comparison, but it would be interesting to see what proportion of catches (or at least sets / hours) originally came from waters inside the PMNM. Perhaps the georeferenced catches from NOAA Observer data can provide insights into this (if not for the entire fleet, at least for the 20% quasi-random subset), or we can use GFW data to see if the proportion of fishing hours inside PMNM roughly corresponds to 10M in revenues (we can test different

“catch rates” to account for the fact that catches inside vs outside may not map 1:1). Perhaps this catch efficiency ratio can be extracted from the NOAA Observer data?

On aggregate the fleet brought in more money in 2015 and 2016 than in previous year, but you discuss the possibility that the distributional effects of this might be different. I would assume that vessels who fished the most in the PMNM area were the ones who took the toughest hit. If possible, it might be interesting to briefly look at distributional effects for the discussion.

Total costs (TC)

So far this section describes the available data, but it’s not clear whether the empirical strategy is fully developed. Just like the datasets, there isn’t a single best analysis that provides the answer, but looking at it from as many angles as possible might help paint a full picture of the effects that vLPAs have had. Here I provide some ideas in which we could use the two main datasets (NOAA and GFW data) to indirectly test the claims made by the fleet.

TC from NOAA Observer program

You mention that a drawback of this dataset is that you only observe fishing events, and not the entire trip (*i.e.* the search and travel). It might be worth looking into combining this with GFW data. NOAA observer program would provide real fishing events (as opposed to the ones predicted by GFW’s neural net), and GFW would provide the entire track. Given that NOAA data cover 20% and GFW only contain 60 boats, we will not get full coverage. If this doesn’t yield better data, it would at least help determine if the three-day space between sets is an appropriate way of grouping them into “trips”.

Results in your table 3 suggest that there’s been a change of ~ 20 miles (positive or negative depending on model specification), and not significant. Perhaps linking this data to GFW would provide full tracks (of a smaller portion of the fleet) to then account for distance between fishing points but also during the search and set activities.

TC from GFW Data

We could also test the increased cost claim by looking at the almost 60 vessels and calculate an estimate of fuel consumption (following Sala et al. (2018)), which, paired with fuel prices, might provide cost estimates¹. Initially this would just be a regression with a policy dummy (and appropriate vessel- and month-level FE’s). We could look into GFW data to identify plausible counterfactuals to include a control group².

¹Of course, there are additional costs (*e.g.* crew, ice, bait, gear), but fuel should represent a large portion of this and should scale with some measures of fishing effort (time and distance). If this is not enough, the previous comparison of catches (sets) that came from PMNM waters before the implementation could provide some insights.

²GFW increased coverage when they added from more satellites, particularly towards the end of 2016 and throughout 2017, I believe. I think it would be important to use counterfactuals in any GFW-related analyses to account for the expected temporal trend in increased effort.

PIPA and Palau

The current approach is to estimate what percentage of fishing effort from the PNA was displaced by PIPA and use this to infer something about Palau. While this provides a measure of the displacement, it does not fully address the possibility of costs increasing. I believe we can use individual tracks (as opposed to just the gridded effort) and obtain show how their behavior changed (*i.e.* are they fishing further away, are they fishing more, where are they now?).

As I mentioned in the call, I have been working with vessels who fished in PIPA as part of my PhD research. In total there are 235³ vessels that have fished within PIPA waters. From these, 206 did so at least once before 2015 and on average exerted $466.8230453 \pm 584.0302142$ hours each year. A significant number of these vessels fished in PIPA and adjacent waters. We can see where they fished before and track where they went after 2015.

In this section I present some of the preliminary results of regressions similar to what you have conducted for US MNMs using hours as an estimate of fishing effort. First, I explore patterns of fishing effort only inside PIPA (Fig. 1). Consistent with the blue paradox, we see an increase in the number of vessels, total hours, mean hours, and number of data points between 2014 and 2015. Shortly after that, all measures decrease in 2015⁴.

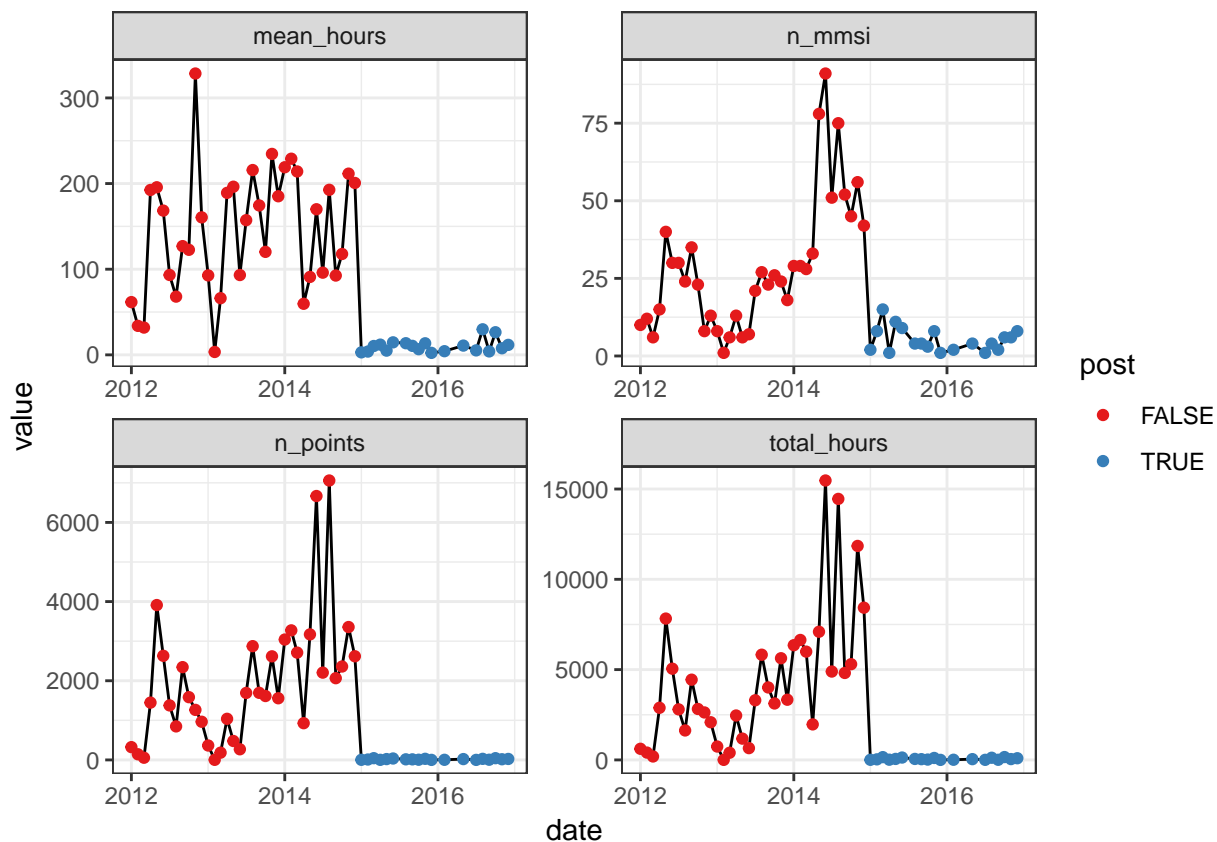


Figure 1: Monthly hours, number of vessels, and data points observed inside PIPA. These clearly show the blue-paradox effect.

³Perhaps some of these vessels only fished there for a couple hours one year. Therefore, I would need to further identify which ones were transient vs local using some cutoff. For now, I use run regressions for all vessels and for vessels that fly the Kiribati flag ($n = 12$). The true number lies between these two groups, but it provides a starting point.

⁴See McDermott et al., (*in review*) for further information

Then, I look at the entire fishing effort of vessels that fished at least once in PIPA before 2015. In other words, I use GFW data to track vessel-level activities inside and outside PIPA before and after 2015. However, all boats included in this case fished at least once in PIPA before 2015 (*i.e.* no control group). First I look at vessels whose mmsi code starts with 529, indicating that they come from Kiribati.⁵ The overall pattern for fishing time (total and mean) show a downward trend that initiated well before 2015 (Fig. 2). The number of vessels as given by unique mmsi numbers shows a maximum near the end of 2014, and then decreases after 2015.

Given the similar trends observed in total fishing hours and mean fishing hours, I calculate total fishing hours at the year-month-vessel level and regress that on a `post` dummy that indicates years before or after 2015. Results of this regression are presented in Table 1. In this table, column (1) presents the regression only against the policy dummy, column (2) includes month fixed effects, column (3) includes month and year fixed effects, and column (4) includes month, year, and vessel fixed effects. All three specifications show negative coefficients. The full model explains 71% of the variance in monthly fishing hours by vessel. This specification has the lowest policy coefficient (labeled `post`), and it is not different from zero at the $\alpha = 0.05$ level.

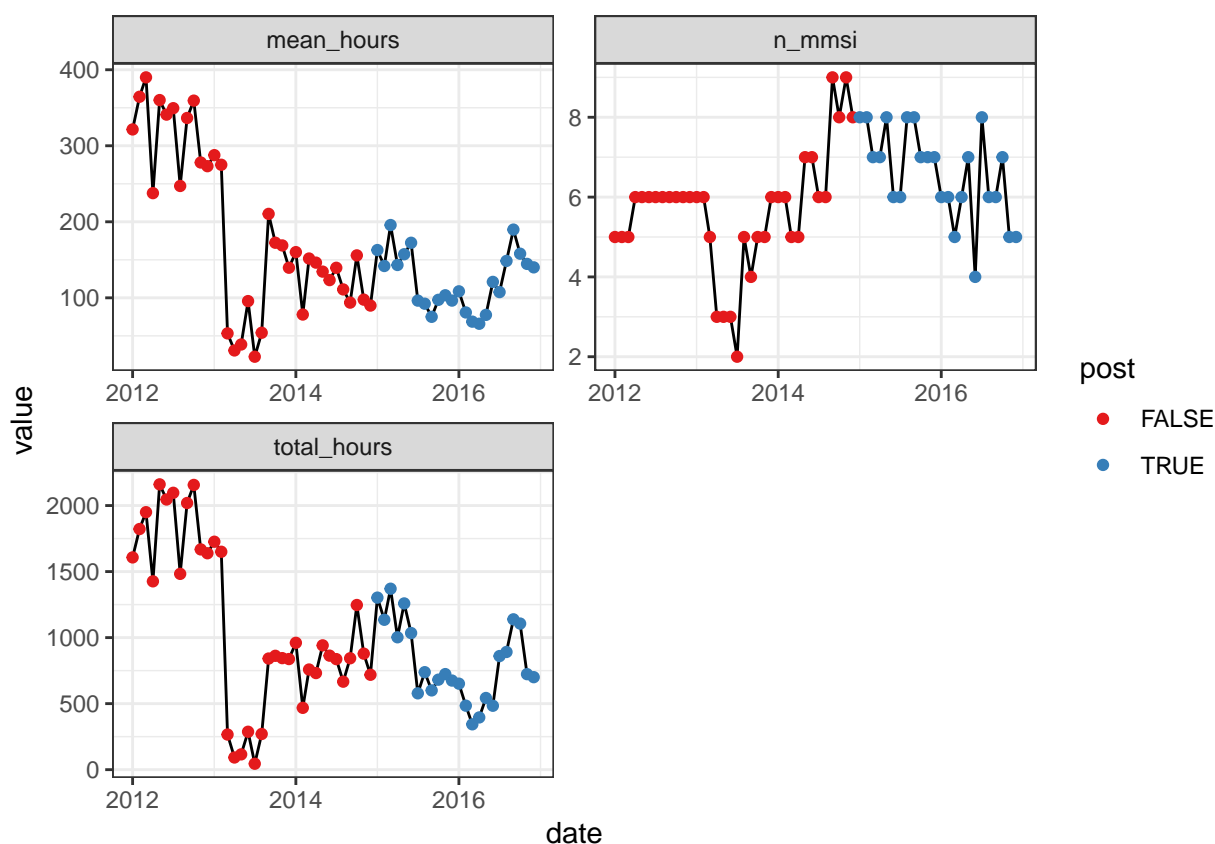


Figure 2: Fishing hours and number of 12 Kiribati vessels from 2012 - 2016 that at some point fished inside PIPA.

⁵link: <http://www.vtexplorer.com/mmsi-mid-codes-en/>

Table 1: Fishing hours from GFW for vessels flying Kiribati flag ($n = 12$). Asterisks indicate significance levels. Numbers in parenthesis represent heteroskedastic-robust standard errors.

	<i>Dependent variable:</i>			
	hours			
	(1)	(2)	(3)	(4)
post	-72.309*** (18.869)	-72.753*** (19.242)	-203.852*** (37.044)	-9.806 (24.365)
Constant	195.230*** (17.485)	234.409*** (38.908)	363.646*** (46.759)	570.869*** (49.981)
Month FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Vessel FE	No	No	No	Yes
Observations	362	362	362	362
R ²	0.032	0.043	0.159	0.714
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01		

I then repeat a similar analysis but for all fishing vessels that fished at least once inside PIPA before 2015. In this case this likely represents an underestimate of the effect, as it could include vessels who once fished inside PIPA, but are not even in the region any more. The number of unique mmsi codes (Fig. 3) follows a similar pattern as in the previous case. However, mean hours and total hours show stable trends before and after. As opposed to only Kiribati vessels who seemed to reduce the number of fishing hours, a similar analysis of all vessels shows positive coefficients that are not statistically significant ($\alpha < 0.05$). Results of the regressions are shown in Table 2. Like before, column (1) presents the regression only against the policy dummy, column (2) includes month fixed effects, column (3) includes month and year fixed effects, and column (4) includes month, year, and vessel fixed effects.

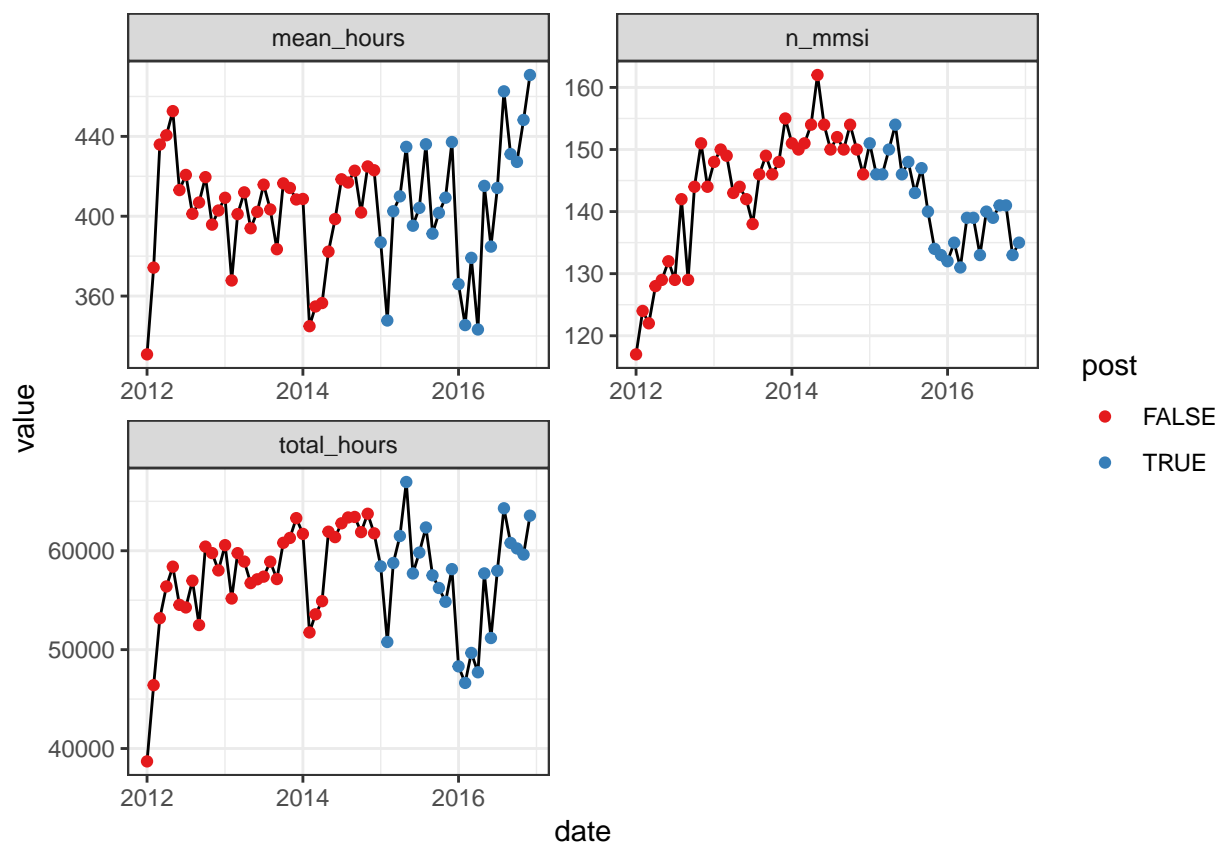


Figure 3: Fishing hours and number of vessels by month for all vessels that fished inside PIPA at least once.

Table 2: Fishing hours from GFW for all vessels (n = 206) that at some point fished in PIPA. Asterisks indicate significance levels. Numbers in parenthesis represent heteroskedastic-robuste standard errors.

	<i>Dependent variable:</i>			
	hours			
	(1)	(2)	(3)	(4)
post	4.163 (5.588)	4.578 (5.574)	0.222 (8.833)	15.783*** (5.829)
Constant	401.848*** (3.792)	381.124*** (9.858)	386.941*** (11.021)	26.919** (13.437)
Month FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes
Vessel FE	No	No	No	Yes
Observations	8,549	8,549	8,549	8,549
R ²	0.0001	0.006	0.006	0.662
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01		

Further work

In order to strengthen this analysis, I would like to identify an appropriate sample of vessels that accurately represent the PNA. This vessels must meet at least these two points: i) belong to the PNA and ii) Have fished for a significant amount of time inside PIPA, to count as “treated”. Ideally, this would get rid of vessels that sporadically fished for insignificant time in PIPA, and are therefore unlikely to be affected. This would include between 12 and 206 vessels (number of Kiribati vessels vs. number of all vessels who fished in PIPA at least once before 2015).

I would also like to explore the possibility of identifying a plausible counterfactual. That way we could do something like a DiD. I think it is possible to identify counterfactual boats. I would start by identifying vessels who meet at least these four criteria: i) fish in near-by regions, ii) have same gear as vessels from PIPA, and iii) having similar length of data, and iv) never fished inside PIPA. Perhaps an additional one would be that they belong to the PNA.

Additionally, run similar regressions on distance traveled, and total vessel hours (not just fishing hours), that could account for the extended “search” time.

Other details

- The introduction states that the main objective is to quantify the economic impacts of vLPAs and compare the cost per hectare to vLPAs on land. I think this would provide an interesting benchmark on cost of conservation per unit area in land vs sea. I would perhaps highlight the part about predicting the possible effects of the Palau MPA.
- I think the novelty of the paper can be highlighted even more. Stevenson, Tissot, and Walsh (2013) evaluated the consequences of fishing displacement from MPAs in Hawaii (a smaller network and totally different fleet). They show that fishing effort was indeed displaced to places further away from ports representing increased costs, but that CPUE also increased. Overall, they don’t find a negative impact on the *perceived* socioeconomic well-being of fishers. However, they do not have plausible counterfactuals and rely on before-after comparisons of perceptions. I think the novelty of this paper is not only the size, resolution, and quality of the data, but the fact that it has a BACI design enabling the identification of the net effect that vLPAs have on fishers. And also the larger contribution to vLPAs (and MPAs in general) literature.
- Recent work by Sala et al. (2018) shows that a large portion of high-seas fishing is only profitable thanks to subsidies. This could compliment White and Costello (2014) and Sumaila et al. (2015) in the introduction.
- “Neither of these datasets is perfect but hopefully combined they will paint a clear picture of what the impact has been”. I find this to be a modest (or humble?) and powerful sentence that highlights the efforts made to identify effects from different sources, and that acknowledges possible data limitations. This sentence should be included alongside the “novelty” in the last paragraph of the introduction.
- Findings by Smith, Zhang, and Coleman (2006) show negative effects, but the reserves were only in place for a short period. I believe they talk about this in their discussion. G. J. Edgar et al. (2014) and Di Franco et al. (2016) show how the effects (at least inside vs outside the reserve) can take up to 10 years.
- Title: “*The economic impact of Large-Scale MPAs*”
- I would be cautious on the interpretation of results by Sumaila et al. (2015). They do show that < 0.01% of catch and landed values come *exclusively* from the high seas, but also that 67% and 72% (catch and value) come from Both EEZs and High seas, and the remaining from EEZs only. Pauly and Zeller (2016) show that ~6% of landings come from the high seas (Fig. 4). It’s perhaps a minor detail, but thought I’d point it out.

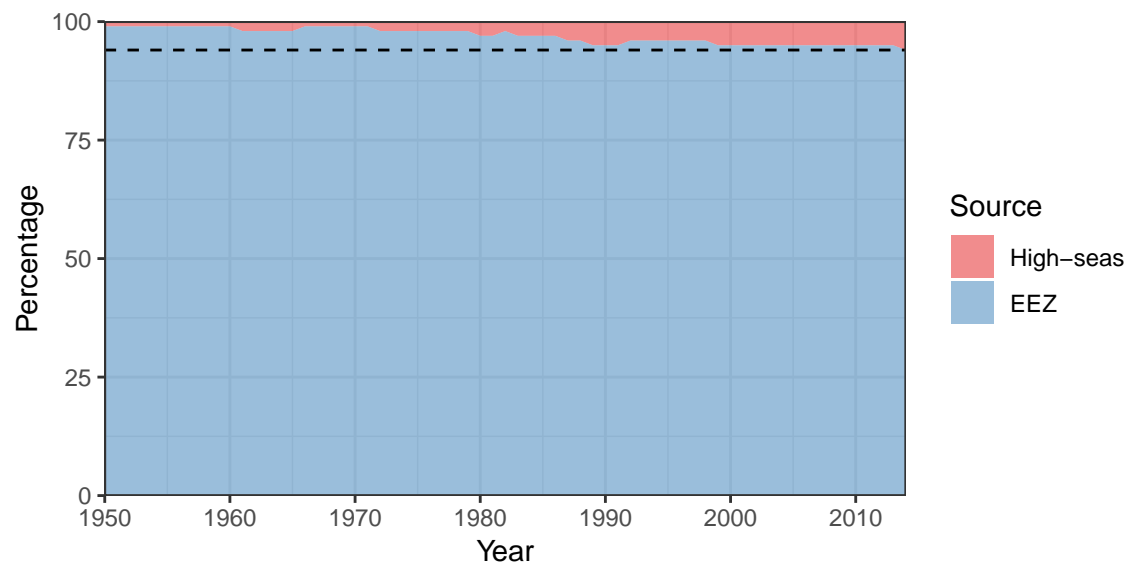


Figure 4: Percentage of catches that come from the high-seas vs. EEZs. (data from Sea Around Us).

References

- Di Franco, Antonio, Pierre Thiriet, Giuseppe Di Carlo, Charalampos Dimitriadis, Patrice Francour, Nicolas L Gutiérrez, Alain Jeudy de Grissac, et al. 2016. “Five Key Attributes Can Increase Marine Protected Areas Performance for Small-Scale Fisheries Management.” *Sci Rep* 6 (1): 38135. doi:10.1038/srep38135.
- Edgar, Graham J., Rick D. Stuart-Smith, Trevor J. Willis, Stuart Kininmonth, Susan C. Baker, Stuart Banks, Neville S. Barrett, et al. 2014. “Global Conservation Outcomes Depend on Marine Protected Areas with Five Key Features.” *Nature* 506 (7487): 216–20. doi:10.1038/nature13022.
- Pauly, Daniel, and Dirk Zeller. 2016. “Catch Reconstructions Reveal That Global Marine Fisheries Catches Are Higher Than Reported and Declining.” *Nat Commun* 7 (January): 10244. doi:10.1038/ncomms10244.
- Sala, Enric, Juan Mayorga, Christopher Costello, David Kroodsma, Maria L D Palomares, Daniel Pauly, U Rashid Sumaila, and Dirk Zeller. 2018. “The Economics of Fishing the High Seas.” *Sci Adv* 4 (6): eaat2504. doi:10.1126/sciadv.aat2504.
- Smith, Martin D, Junjie Zhang, and Felicia C Coleman. 2006. “Effectiveness of Marine Reserves for Large-Scale Fisheries Management.” *Can. J. Fish. Aquat. Sci.* 63 (1): 153–64. doi:10.1139/f05-205.
- Stevenson, Todd C., Brian N. Tissot, and William J. Walsh. 2013. “Socioeconomic Consequences of Fishing Displacement from Marine Protected Areas in Hawaii.” *Biological Conservation* 160 (April): 50–58. doi:10.1016/j.biocon.2012.11.031.
- Sumaila, U Rashid, Vicky W Y Lam, Dana D Miller, Louise Teh, Reg A Watson, Dirk Zeller, William WL Cheung, et al. 2015. “Winners and Losers in a World Where the High Seas Is Closed to Fishing.” *Sci Rep* 5 (1): 8481. doi:10.1038/srep08481.
- White, Crow, and Christopher Costello. 2014. “Close the High Seas to Fishing?” *PLoS Biol* 12 (3): e1001826. doi:10.1371/journal.pbio.1001826.