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ENSO increases foreign fishing*

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November 14, 2018

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Abstract

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Illegal, unreported and unregulated (IUU) fishing contributes to x% of the global fishing economy [1]. Foreign fishing in a nation's Exclusive Economic Zone (EEZ) contributes to a y% of IUU fishing [2]. Drivers of foreign fishing include a, b and c, but it is unclear how this may change under climate change. We show ENSO events increase foreign fishing by z%. We also find the effect is lower for more adaptive gears such as longliners. This quantitative evidence linking climate and fishing behavior have important implications for climate projections and adaptation of this sector.

*Work in progress; do not circulate.

¹⁵ 1 Introduction

¹⁶ Fisheries are an important source of food, livelihoods, local and national economies [3]. A grow-
¹⁷ ing body of literature highlights how climate impacts could reduce catch [4, 5] and theoretically
¹⁸ incentivize overfishing or illegal fishing as stocks shift their distributions [6]. Empirical evidence
¹⁹ has been limited to case studies (CITE). However, advances in technology allow us to understand
²⁰ fishing behavior [7, 2, 8].

²¹ Satellite data using an automatic identification system (AIS) allows us to see where individual
²² boats go, and infer when fishing events occur [7]. Recent studies have captured how policies, such
²³ as banning foreign fishing [2] and the creation of Marine Protected Areas have impacted illegal,
²⁴ unreported and unregulated fishing (IUU) [8]. The high-resolution data also lends itself well to
²⁵ exploring how the physical environment impacts fishing behavior.

²⁶ There is a large literature on how highly migratory stocks such as tuna move with sea-surface
²⁷ temperatures [9] and has been empirically shown to move during El Niño and La Niña events
²⁸ [10]. Theoretically fishing fleets could follow the stocks. However, limitations in fishing jurisdic-
²⁹ tions such as Exclusive Economic Zones (EEZ) and Marine Protected Areas (MPAs-SHOULD WE
³⁰ EXPAND THE ANALYSIS TO MPAs) may impact their decisions on where to fish. We do not
³¹ know if fishing fleets tend to reduce fishing during El Niño/La Niña, or make the costly decision
³² to increase fishing in foreign waters (and protected areas).

³³ Using publicly available data through the Global Fishing Watch (GFW) initiative, we docu-
³⁴ ment how purse seine and longline fleets respond to El Niño and La Niña years, where local en-
³⁵ vironmental conditions are more extreme. We do this by segmenting the ocean into treatment
³⁶ and control regions, where treatment regions are regions whose local environmental variables are
³⁷ correlated to ENSO and control regions have no correlation between the local environment and
³⁸ ENSO (See Methods 3.1.4). We then compare the number of hours vessels fish in foreign waters
³⁹ during neutral ENSO months to El Niño and La Niña months in treatment regions and control
⁴⁰ regions (See Methods 3.1.3).

41 **2 Results**

42 Let's go through the results

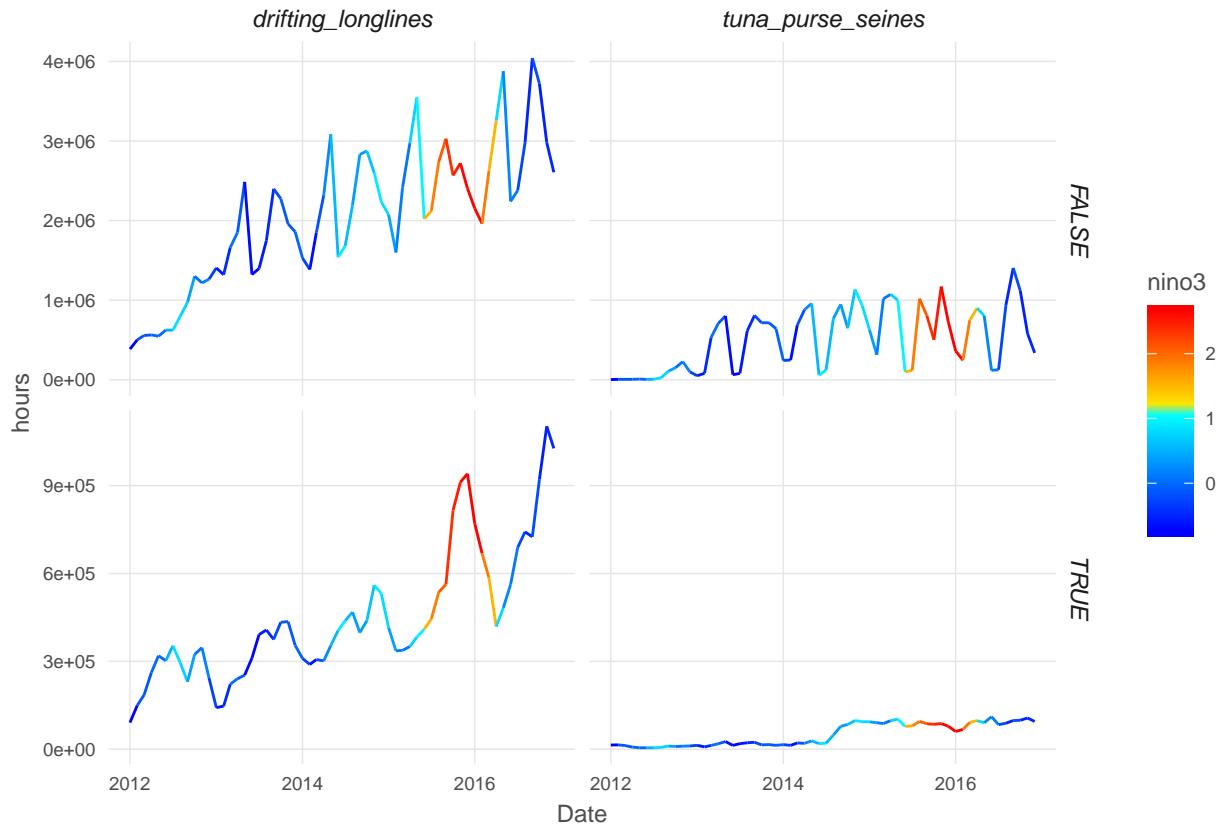


Figure 1: Trends in fishing hours by gear and foreign

Table 1: Foreign fishing hours and nino3

	Dependent variable:							
	hours				hours2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
nino3anom	1.202*** (0.088)	1.194*** (0.088)	0.891*** (0.089)	0.412*** (0.089)	0.047*** (0.002)	0.047*** (0.002)	0.036*** (0.002)	0.020*** (0.002)
treated	1.495*** (0.137)	1.448*** (0.137)	1.785*** (0.138)	-2.374*** (0.177)	0.122*** (0.004)	0.122*** (0.004)	0.132*** (0.004)	-0.027*** (0.005)
nino3anom:treated	0.704*** (0.117)	0.798*** (0.117)	0.799*** (0.117)	1.202*** (0.117)	0.014*** (0.003)	0.014*** (0.003)	0.019*** (0.003)	0.048*** (0.003)
Constant	27.895*** (0.109)	28.202*** (0.110)	31.000*** (0.245)	27.247*** (1.189)	3.422*** (0.003)	3.422*** (0.003)	3.555*** (0.007)	3.452*** (0.033)
Gear FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	No	No	Yes	Yes
Country FE	No	No	No	Yes	No	No	No	Yes
Observations	415,884	415,884	415,884	415,884	415,884	415,884	415,884	415,884
R ²	0.002	0.003	0.008	0.023	0.006	0.006	0.016	0.041

Note:

*p<0.1; **p<0.05; ***p<0.01

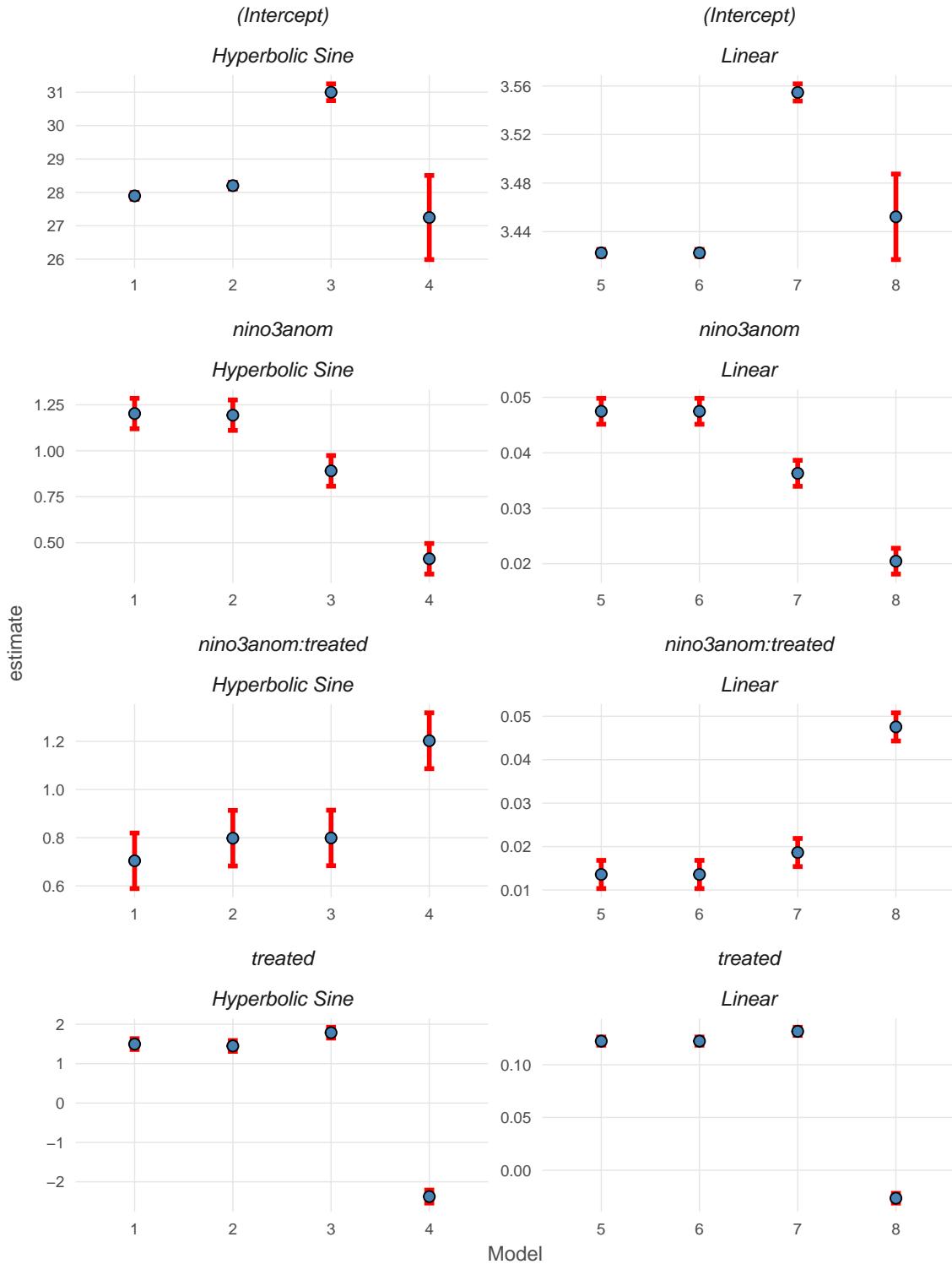


Figure 2: Coefficient estimates for the models ran above. Graphs on the left show estimates after the hyperbolic sine transformation of hours. Right side show no transformation of hours. Model numbers (x - axis) correspond to the columns in table 1 (1 - 4) and table 2 (5 - 8).

43 **3 Discussion**

- 44 Purse seiners: More regulation, gear can't go as deep Long-liners: Less regulated, but gear can go
45 deeper Trawlers: Are species as impacted by ENSO events?

46 **3.1 Methods**

47 **3.1.1 Global Fishing Watch data**

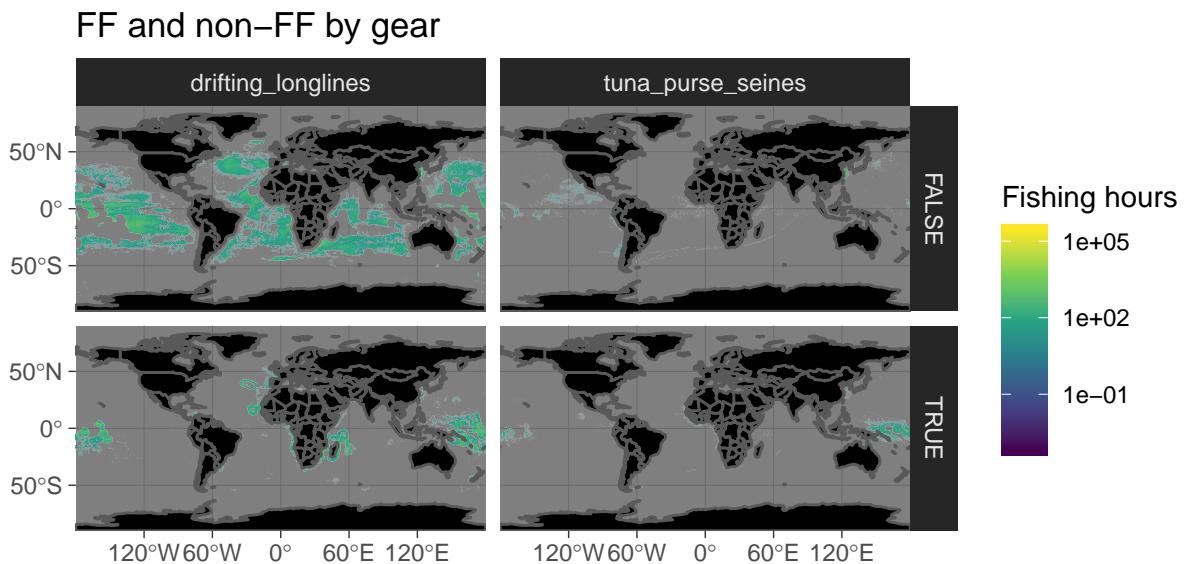


Figure 3: Fishing effort (hours) by gear and foreign fishing

48 3.1.2 El Niño-Southern Oscillation

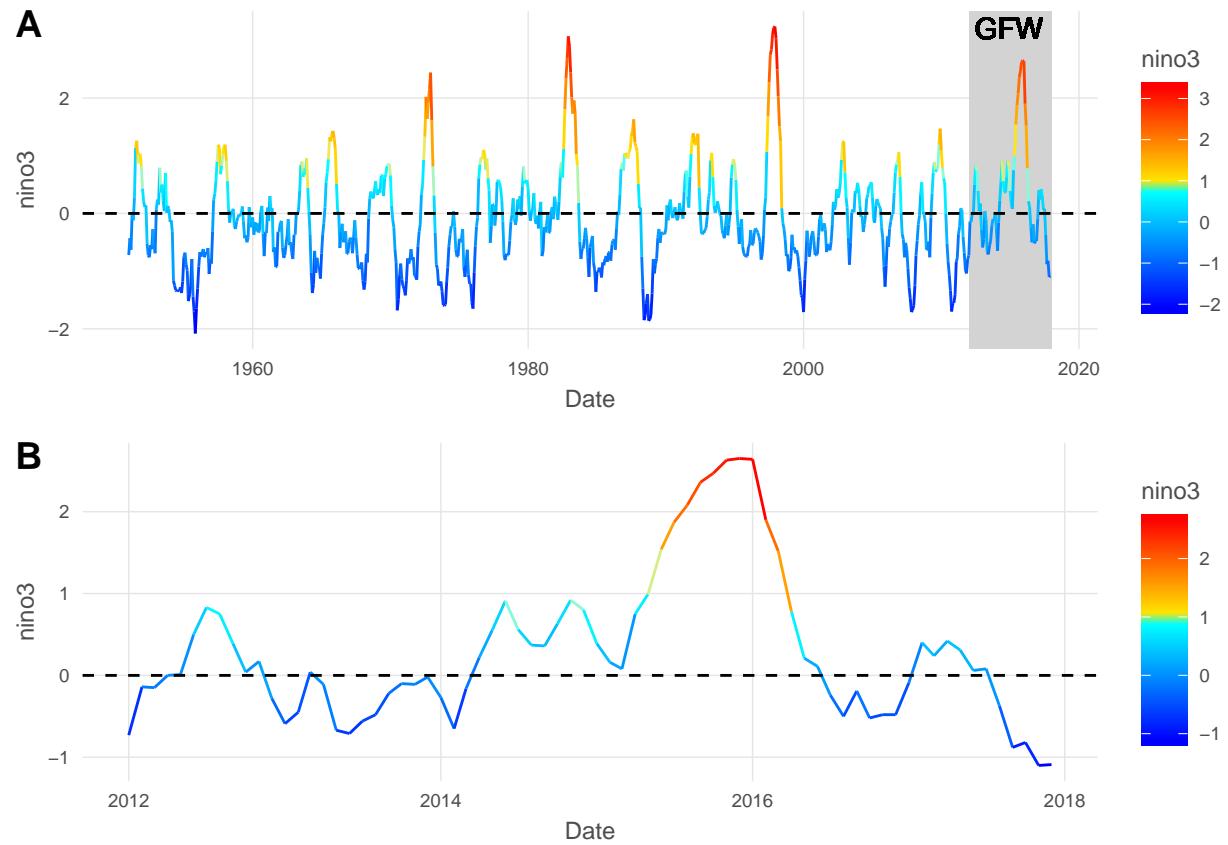


Figure 4: Timeseries of nino3 index (detrended) for A) The entire length and B) timespan matching GFW data

49 **3.1.3 Empirical specifications: ENSO and Foreign Fishing**

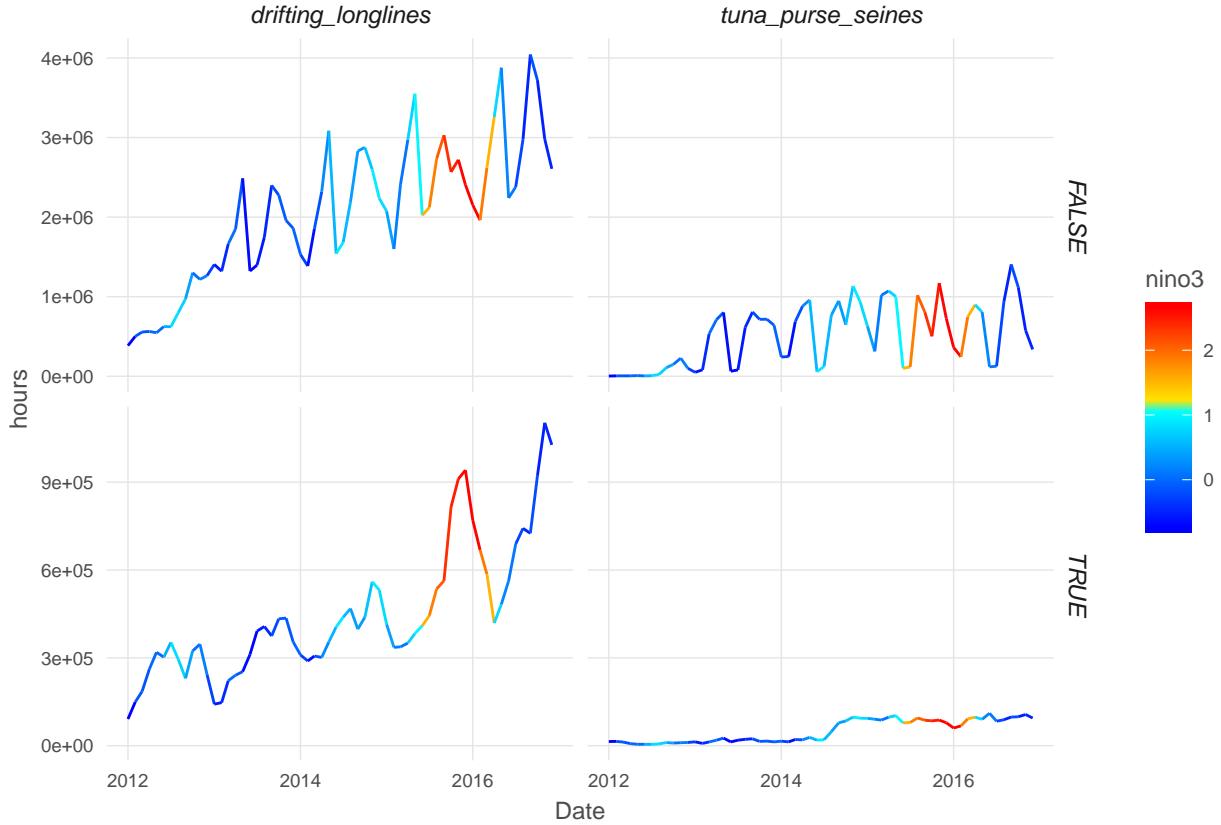


Figure 5: Trends in fishing hours by gear and foreign

50 We estimate the effects of ENSO on Foreign Fishing using a difference-in-difference strategy to
 51 compare the effects of ENSO on foreign fishing in regions impacted by ENSO to its effects on
 52 foreign fishing in regions not impacted by ENSO.

$$\log(FF_{ct}) = \alpha + \beta ENSO_t \times \mathbb{I}_{c\epsilon T} + \phi_t + \lambda_c + \epsilon_{ct} \quad (1)$$

53 FF_{ct} represents the foreign fishing variable of interest by country and year. We use an inverse
 54 hyperbolic sine¹ of our foreign fishing variable in my main specification to transform zeroes in my
 55 data [11, 12]. α is a constant and β captures the linear effect of ENSO on countries in effected
 56 regions compared to counties in regions unaffected by ENSO. The treatment is ENSO interacted

¹ $\ln(FF + \sqrt{1 + FF^2}) \rightarrow \ln(2L)$

57 with a dummy, \mathbb{I}_{ceT} , that equals 1 for countries in ENSO-effected regions and 0 for counties in
 58 uneffectected-ENSO regions. ϕ_t are monthly fixed effects and λ_c are country fixed effects. Standard
 59 errors are clustered at the country level.

60 **3.1.4 Empirical specifications: Identify treatment regions**

61 First we established a relationship between ENSO and two local environmental variables that
 62 drive the geographical presence of fish stocks, sea-surface temperature (SST) and windspeed. We
 63 obtain an average monthly SST value, SST_t , for each grid-point from the NOAA OI SST Dataset
 64 within the spatial bounds of each fishery as defined by the NEFSC (see fig. 1 in main text). We
 65 run the following regression model:

66 NOTE: WE MAY NOT NEED TO DETREND SST

$$SST_t = \omega + \phi ENSO_t + \sum_{p=1}^N \mu_p t^p + \epsilon_t \quad (2)$$

67 where ω is a constant, ϕ captures the linear effect of monthly ENSO and μ_p captures the effect
 68 of a pth-order polynomial time trend. Standard errors use the Newey-West adjustment which al-
 69 lows for serial correlation and heteroscedasticity of arbitrary form in the error terms over an opti-
 70 mally chosen window of time [13, 14]. SST during this sample period exhibited trending behavior
 71 and thus needed to be detrended. To determine the polynomial order of the time trend, N , we
 72 use the Akaike Information Criteria (AIC) [15], which when minimized captures a model's over-
 73 all goodness of fit while penalizing additional terms with limited explanatory power. For both
 74 fisheries, we observe that the AIC statistic drops when a time trend of second-order or higher
 75 is included in Equation 2. Importantly, we detect a positive/negative relationship between win-
 76 ter ENSO and SST and a positive/negative relationship between winter ENSO and windspeed,
 77 shown in Figure 1.

$$\log(FF_t) = \psi + \delta ENSO_t + \sum_{p=1}^N \kappa_p t^p + \mu_t \quad (3)$$

78 ψ is a constant; δ captures the linear effect of ENSO and κ_p represents the effect of a p^{th} -order
 79 polynomial time trend. Standard errors use the Newey-West adjustment, allowing for arbitrary

- 80 forms of serial correlation and heteroscedasticity in the error term with a bandwidth of 10 months.
- 81 As a robustness check, we use different polynomial time trends to remove any long-term trends.

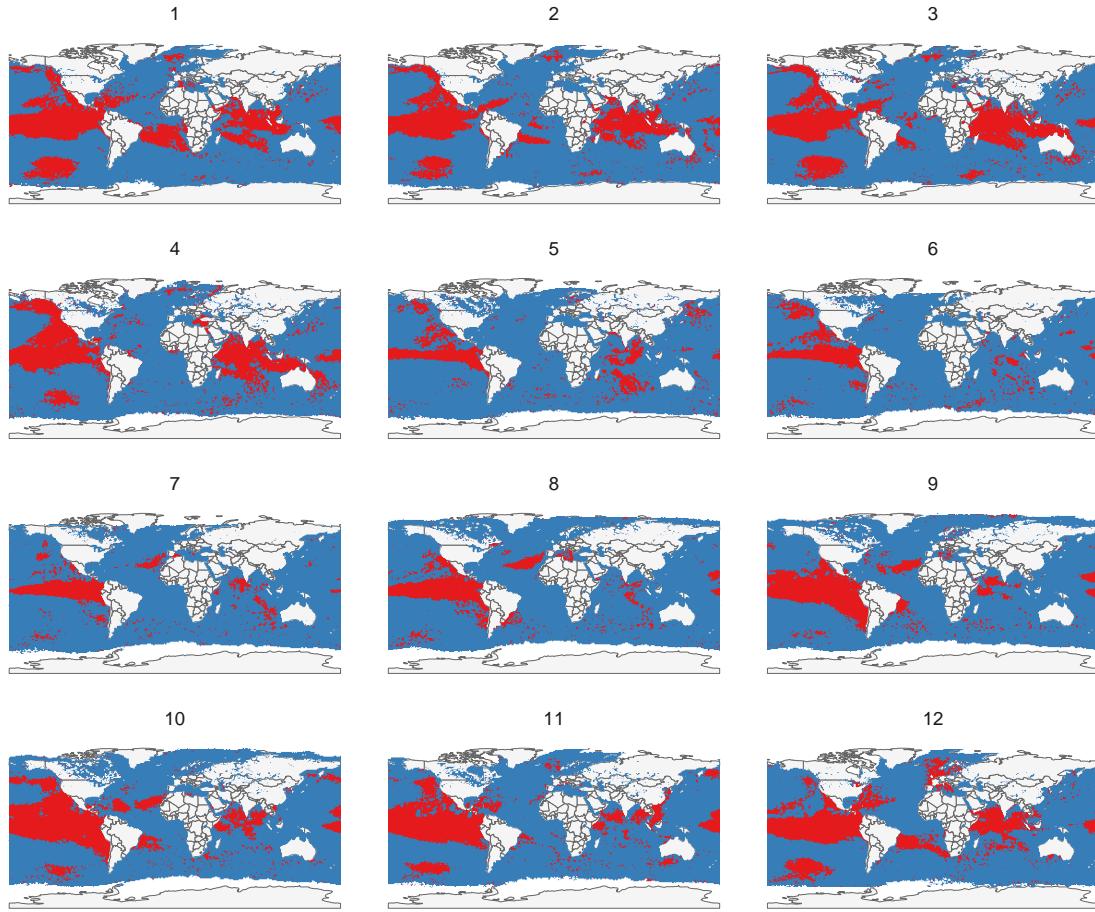


Figure 6: Monthly correlations between SST and nino3 index. Numbers above each panel indicate the month (1 = Jan, 12 = Dec). Red zones indicate the pearson's correlation coefficient was > 0 and $p < 0.1$.

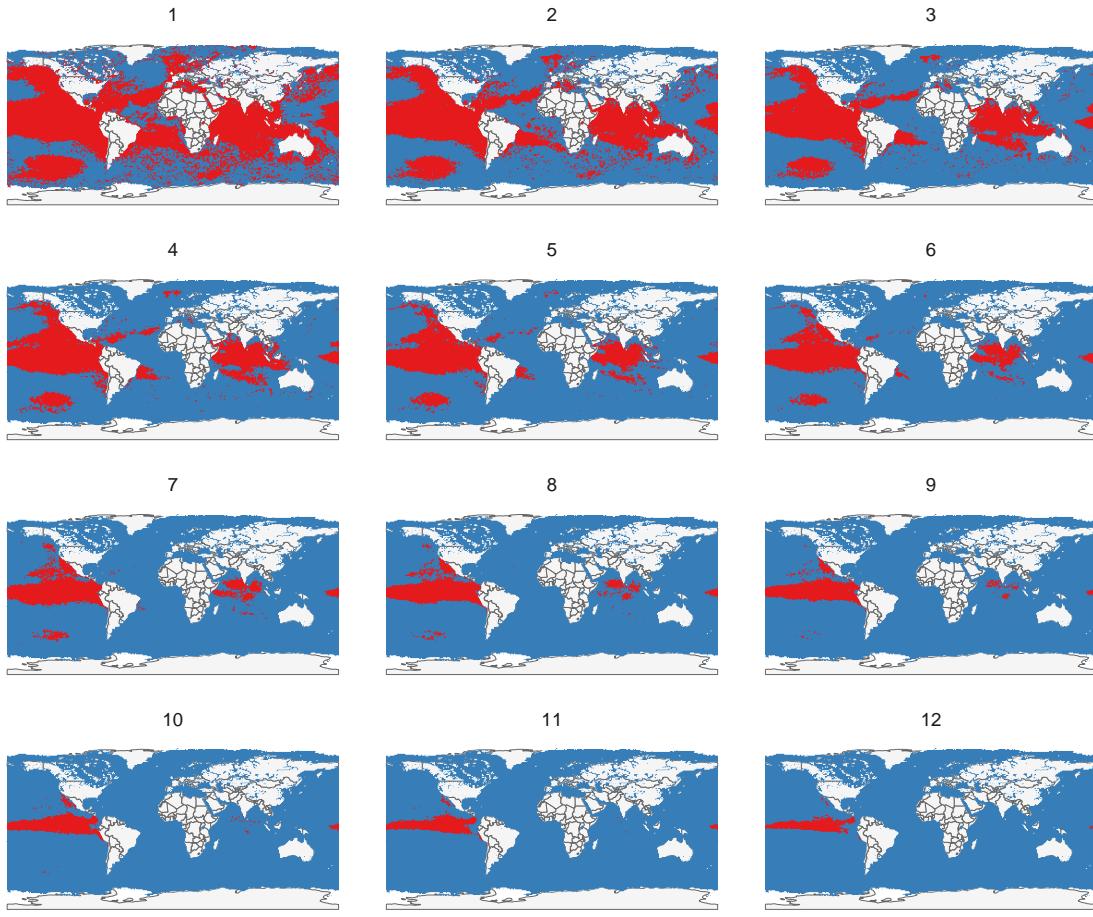


Figure 7: ENSO teleconnection depending on number of months. Number above figures indicate the minimum number of months for which a particular parcel was correlated to nino3 (red). For example, the panel 6 indicates that all red regions where SST showed a positive ($r > 0$) and significant ($p < 0.1$) correlation with nino3 index for at least 6 months.

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115 **Acknowledgements** We thank Christopher Costello and Steve Gaines for their helpful com-
116 ments and suggestions. should be addressed to (email:).