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RESEARCH ARTICLE

How climate change and climate variability affected trip distance of a commercial fishery

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Abstract

Changes in climate factors affect the distribution of various tuna species differently due to their unique physiological adaptations and preferred habitats. As the resulting spatial distributions of tunas alter in response to climate change and climate variability, the distribution of fishing effort will, in turn, be affected. This study uses a quantitative model to estimate the impacts of SST and ENSO events on trip distance of the Hawaii deep-set longline fleet between 1991 and 2020. The results show that the higher the SST of the fishing grounds of the Hawaii longline fleet, the longer trip distance; whereas ENSO events could result in shorter trip distance, possibly due to changes in catch rates of different tuna species through spatial redistribution during El Niño and La Niña events.

Introduction

Impacts of climate change and climate variability on commercial fisheries are widely studied, and focus primarily on changes to fish biomass [1–10] and spatial distribution of marine species [1, 6, 7, 11–21]. Although humans are an important component of marine ecosystems, few studies have examined how climate change and variability impact fisher behavior [22–27]. Haynie & Pfeiffer [23, 24] stressed the importance of including fisher behavior in predicting the impacts of climate change on fisheries due to the complex interactions between fisher behavior and marine ecosystems. In particular, spatial distribution of fishing is influenced by the interactions of "physical, biological, and economic mechanisms" [24]. Rising ocean temperatures and El Niño-Southern Oscillation (ENSO) events could influence the spatial distribution [1, 6, 7, 11, 17–20, 28, 29], abundance [1, 7, 9, 17, 20], and catchability [1, 6, 11, 19–21, 30–33] of highly migratory species like tuna as different species have different spatial responses to climate change and variability due to their unique physiological adaptations and preferred habitats [6, 19, 34–36]. As a result, fisheries that target different tuna species could be affected correspondingly by climate change and variability [6, 19].

Studies have shown that locations of commercial tuna fisheries are influenced by climate change and climate variability [6, 19, 20, 30, 37], and despite humans being an important part of marine ecosystems [23, 24], no study has quantified the spatial reaction of fishers who target tuna in relation to climate change and climate variability. The Hawaii longline fishery provides a good case study to examine the impacts of climate factors on fisher behavior. Hawaii's

operations information. Data from the Hawaii longline logbook dataset (metadata: https://www.fisheries.noaa.gov/inport/item/2721) are available from the US National Marine Fisheries Service, to researchers who meet the criteria for access to confidential data and agree to abide by non-disclosure standards of US NOAA Administrative Order 216-100 on Protection of Confidential Fisheries Statistics. Requests for the data can be sent to Keith Bigelow, Data Steward of Hawaii longline logbook dataset, at keith.bigelow@noaa.gov.

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centralized location in the North Pacific Ocean allows longline vessels the flexibility to go in any direction as their catches respond to changes in climate. For example, vessels could travel further north or east to cooler parts of the ocean when fishing grounds become warmer and unfavorable for tuna habitat. Vessels could also travel to fishing grounds with higher catch per unit effort (CPUE) driven by ENSO events [30]. In addition, a long time series (30-year period) of fishery-dependent data, environmental variables, and climate indices are available for empirical modeling. The main purpose of this study is to examine how climate factors have affected the Hawaii longline vessels' trip distance; specifically, the interactions of climate with tuna species' spatial distributions and catch rates and the subsequent impacts on vessels' trip distance are evaluated. As trip distance has a direct relationship to fuel cost, the most important variable cost item in the Hawaii longline fishery [38], any changes in trip distance would directly impact the economic performance of the fishery.

This study examines the relationships between climate factors and vessels' trip distance for the Hawaii deep-set longline fishery over a 30-year period (1991–2020). This period was characterized by rising ocean temperatures and multiple strong and mild El Niño and La Niña events in the Pacific Ocean. During this period, the Hawaii longline fishery expanded both fishing efforts and fishing grounds [39, 40], despite policies limiting access to particular areas [41]. Understanding the past relationships between climate factors and trip distance may help predict the impacts of climate change and climate variability on future fishing operations and the subsequent economic effects, such as changes in fishing costs and net revenue. This information can be used to advise fisheries management strategies.

Though few studies have developed models to quantify the effects of climate change and climate variability on fisher behavior, such as trip distance, Haynie & Pfeiffer [23] examined the effect of the size of cold pool (a pool of arctic water that remains cold ($< = 2^{\circ}C$) and occurs near the seafloor of the Bering Sea forming a barrier for a variety of species) on trip distance in the Bering Sea walleye pollock fishery. Using a similar approach as Haynie & Pfeiffer [23], this study incorporates two climate factors that are widely recognized as drivers affecting fishing location of commercial fisheries in the Pacific Ocean: sea surface temperature (SST) and ENSO events, to develop a model that quantifies their influence on the trip distance of Hawaii deep-set longline fishery. The model also incorporates other important factors that may affect trip distance including diesel price, quarterly biomass controlling seasonal fishing patterns, management policies that directed the fishing location access, temporal variations, and vessel-specific fixed effects.

Materials and methods

Fishery, climate change, climate variability, and tuna distribution

The Hawaii deep-set longline fishery operates primarily outside the U.S. Exclusive Economic Zone (EEZ) in the North Pacific Ocean (from 180˚W to 120˚W and from equatorial waters to around 40˚N), targeting bigeye tuna (*Thunnus obesus*), with little foreign competition [40]. Honolulu is the major port for the Hawaii longline fishery. In 2019, it was the 9th largest commercial fishing port in terms of landing value, and 23rd largest in terms of landing volume [42]. The scale of the fishery, in terms of number of fishing sets, and the fishing grounds have expanded tremendously over a 30-year period (Fig 1). The temporal and seasonal changes in fishing locations were related to oceanographic and environmental conditions that affected catch rates [39, 40]. The operational aspect of the fleet includes deploying deep-set hooks early in the morning and hauling in the afternoon or evening [43, 44]. Hook depth was set between 100 m and 400 m [43], overlapping the vertical habitat of bigeye tuna during daytime (200 m to 400 m below the surface) [44, 45], with most bigeye tuna caught at depths greater than 200

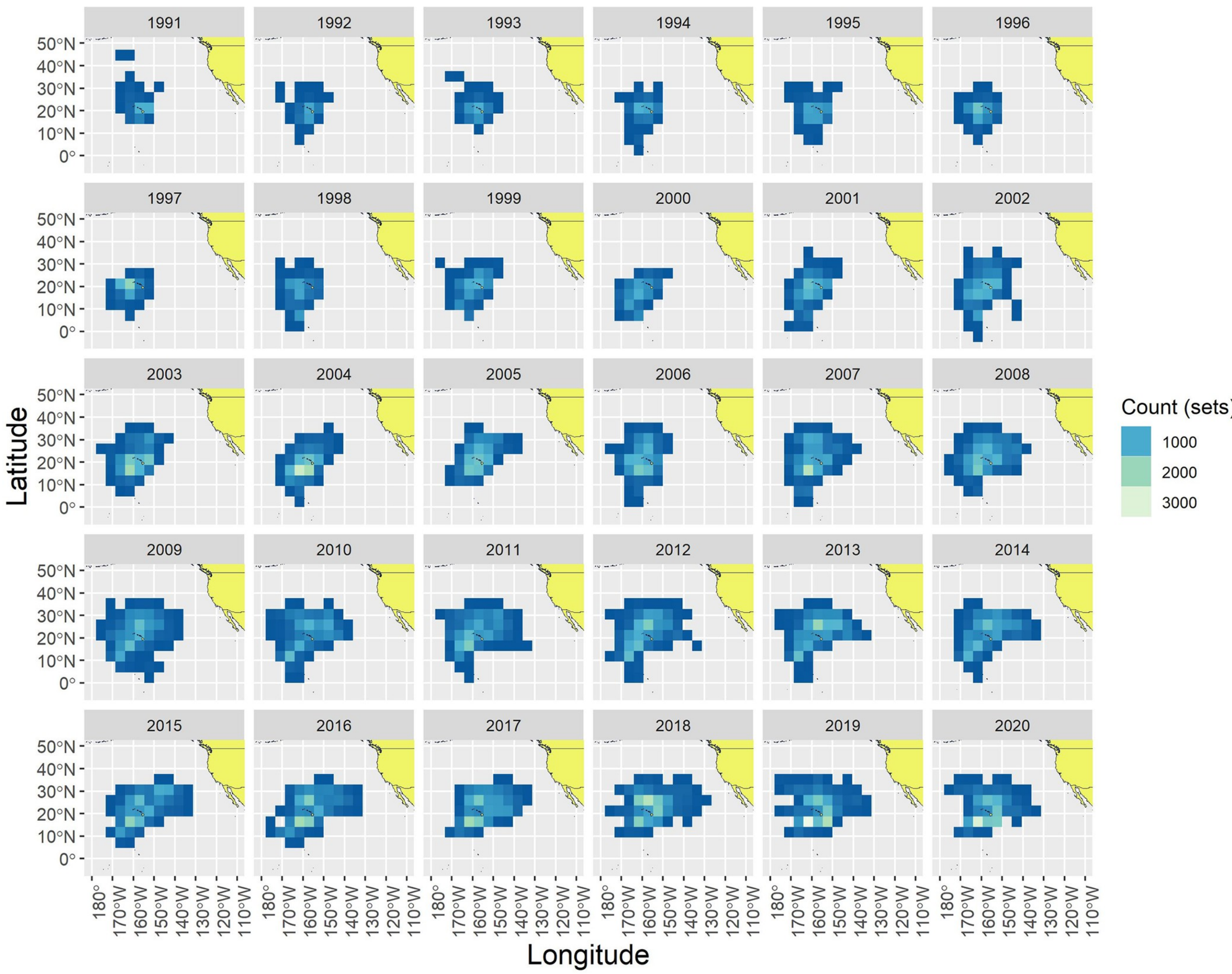

Fig 1. Spatial extent and density of fishing sets of Hawaii deep-set longline fishery, 1991–2020. Note: Only included trips that departed from and returned to the Honolulu port. Data records with effort by less than three individual vessels in 5˚ x 5˚ in a day were removed to meet confidentiality requirements.

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m [44]. The vertical overlap of bigeye tuna swimming depth and deep-set longline gear has a direct impact on bigeye catch rates in the Hawaii longline fishery [28, 40, 44, 45]. With increasing ocean temperatures and ENSO events changing the thermal structure and oxygen concentration in different parts of the Pacific Ocean [7, 29, 33, 46, 47] and altering the spatial distributions of tuna species [6, 7, 11, 17–20, 28, 29], it is reasonable to expect that changes in climate factors would also impact tuna catch rates and spatial operations of the Hawaii longline fleet.

Effects of climate change and climate variability on tuna distributions

There is evidence that ocean warming has shifted the tuna distribution poleward by 6.5 km per decade in the northern hemisphere [17]. In the past four decades (1960–2011), the percentages of skipjack tuna (*Katsuwonus pelamis*) and yellowfin tuna (*Thunnus albacares*) caught by longliners have shifted from tropical to subtropical areas in the Pacific Ocean during periods of increased SST [11]. Climate change and variability are expected to continue to affect tuna biomass, distribution, and subsequently fishing patterns. Senina et al. [9] projected that, in the areas where the Hawaii longline fishery currently operates, climate change impacts alone (without fishing) would decrease bigeye tuna biomass up to 18% in the western and central Pacific Ocean (WCPO), and increase bigeye tuna biomass by 8% in the eastern Pacific Ocean (EPO) during the 21st century. Focusing on the effect of climate change on the Hawaii longline fishery, Woodworth-Jefcoats et al. [10] projected that ocean warming alone would lower the bigeye tuna biomass by 20% by 2100 because rising ocean temperatures reduce plankton biomass, and thus food available to predators. Tuna and billfish species richness was projected to shift northward and eastward in the North Pacific Ocean, potentially shifting the Hawaii longline fishery's fishing activities further from the port in Hawaii or changing the homeport to the mainland west coast.

Many studies confirmed that ENSO events affected the preferred habitat and distribution of different tuna species in the Pacific Ocean vertically [6, 19, 21, 28, 29, 46], horizontally [6, 7, 18–20, 30, 48], and northward [21, 47]. Historical data also showed changes in tuna catches associated with ENSO events [6, 19–21, 28, 30, 33]. ENSO events have led to uneven changes in the vertical thermal structure and vertical extension of tuna habitats across the Pacific Ocean and have induced changes in the spatial distributions of different tuna species due to their unique physiological adaptations and preferred habitats. The preferred depth of adult bigeye is mainly below the thermocline [44, 49], while the preferred depth of yellowfin, skipjack, and albacore (in temperate latitude) is above the top of thermocline [50–54]. During El Niño events, the thermocline flattens across the equatorial Pacific, rises in the western Pacific, and deepens in the eastern Pacific. The opposite happens during La Niña events. Tagging studies in the Pacific Ocean found that bigeye tuna's swimming depth had a strong relationship with thermocline depth, and the deepening of the thermocline in the eastern Pacific during El Niño events was associated with deeper distribution of bigeye [28]. The shoaling of the thermocline (rising of depth of mixed layer) in the western Pacific during El Niño events reduces the depth yellowfin can utilize to search for food as their preferred depth is above the thermocline. When the preferred habitat shrinks due to El Niño events, there is greater vertical overlap between the yellowfin preferred habitat and the depth of surface fishing gear in the western Pacific. During La Niña events, deepening of the thermocline in the western Pacific extends the vertical habitat of bigeye and yellowfin, which decreases their vulnerability to surface gears [6]. Conversely, **s**kipjack tuna are not affected by the changes in thermocline due to ENSO events, as they inhabit the surface layer of the ocean [6]. Several studies found the variations of tuna catch rates were associated with ENSO-induced vertical change in thermal structure. Abascal et al. [28] suggested that the strong El Niño in 2015 that deepened the thermocline in the eastern Pacific could have contributed to the increased bigeye catch rates by the Hawaii longline fleet in that area. In a similar longitudinal region, increased bigeye hook rates were observed by tuna longliners at the western edge of the eastern tropical Pacific Ocean (between 130˚W and 160˚W) during El Niño years, possibly due to the expansion of bigeye's preferred depth habitat in that area [21].

Changes in thermocline also alter the temperature habitats for tuna (temperature at which tuna occur) in different parts of the Pacific Ocean. Temperature habitats for tuna vary by species, with bigeye occurring at the lowest temperature ranges, followed by albacore, yellowfin, and skipjack. Temperature habitat for bigeye is also wider than the other three tuna species [19]. During El Niño events, the shallowing thermocline rises and extends the temperature habitat vertically for tunas in the western Pacific. During La Niña events, the deepening of thermocline deepens and contracts the temperature habitat in the western Pacific [19]. Japanese longline fishery observed higher (lower) bigeye CPUE and lower (higher) albacore CPUE in the western Pacific during El Niño (La Niña) events. This pattern corresponded with the vertical extension (contraction) of temperature habitat for bigeye during El Niño (La Niña) events and the shoaling (deepening) of the temperature habitat for albacore in the western Pacific during El Niño (La Niña) events [19]. Japanese and U.S. purse seine and Japanese pole and line fisheries all observed higher yellowfin catch rates in the western and central Pacific during El Niño events, which was associated with the vertical extension of temperature habitat for yellowfin [19].

Changes in oxygen concentration during ENSO events affect the vertical distribution of tuna, as oxygen is an important factor that alters the vertical habitat space during different ENSO phases [46, 55]. During El Niño events, the low oxygen waters under the thermocline are pulled upward as it gets shallower in the western Pacific and reduces the vertical habitat space, whereas the deepening of thermocline in the eastern Pacific pushes down the low oxygen waters under the thermocline and extends the vertical habitat space [46]. As different tuna species have different limits of oxygen tolerance [35, 36], their vertical habitat spaces vary. Bigeye have a higher tolerance of low dissolved oxygen concentration when compared to other tuna species, allowing them to have a wider vertical habitat [6, 34–36]. Yellowfin and albacore have lower tolerance of low oxygen levels, so lower oxygen in the thermocline would restrict them to surface waters [6, 46]. Skipjack are less vulnerable to changes in oxygen due to ENSO events since they mainly stay above the thermocline due to their high oxygen demand [56], and the ENSO-induced changes in oxygen mainly occur in or below the thermocline [7]. Despite the shoaling of the thermocline compressing the vertical habitat space with lower oxygen in the western Pacific during El Niño events, it expands bigeye's preferred depth habitat, as their high tolerance to low oxygen enables them to access a colder habitat at shallower depths. Howell and Kobayashi [30] suggested the higher bigeye catch rates by the Hawaii longline fishery around the Palmyra Atoll during the winter months of El Niño events could be due to the El Niño-induced changes in oxygen that expand the vertical habitat for bigeye. On the other hand, yellowfin and skipjack have lower tolerance to low oxygen, and as their vertical habitat compresses in the western Pacific, it expands in the eastern Pacific during the El Niño events. One consequence of changing oxygenated vertical habitat is the driving of yellowfin and skipjack eastward toward more favorable oxygen conditions [46]. The decreased oxygen concentration may also decrease the foraging frequency of yellowfin and skipjack at deeper depths during daytime [29]. As the Hawaii longline fleet deploys deep-set hooks in the morning [43, 44], ENSO events could affect the Hawaii deep-set longline CPUE for these species.

ENSO events also shift the tuna habitat and distribution horizontally. During El Niño (La Niña), the western Pacific warm pool moves eastward (westward), causing the Eastern Warm Pool Convergence Zone to move eastward (westward) [57]. Surface tuna, like skipjack, mirror the movement of the convergence zone to prey on the aggregate plankton and micronekton. This may explain the extension of the purse seine fleet to the east, and increased effort in the central Pacific during El Niño events, and in the west of the reduced warm pool during La Niña events [20, 48]. Howell and Kobayashi [30] also suggested the eastward shifts in preferred habitat during El Niño might explain the increase in bigeye catch rates around the Palmyra Atoll by the Hawaii longline fleet. A reverse shift of habitat and decrease in bigeye catch rates in the same region were observed during the onset of La Niña in June 1998 [30]. Studies also found northward shifts in habitats and catches during ENSO events. Zhou et al. [47] found bigeye habitat hotspots developed north of the Hawaiian Islands during El Niño events. Lu et al. [21] found yellowfin hook rates increased in the northern tropical Pacific Ocean, suggesting a northward expansion of yellowfin's preferred habitat during La Niña events.

Data and model

This section first describes the data used for modeling, and then explores the potential relationships between climate factors and trip distance/fishing location of the Hawaii longline fleet. The potential relationships between climate factors and overall catchability, and catchability of different tuna species by the Hawaii longline fleet are also explored. These potential relationships demonstrate the possible connections between climate factors and their impacts on tuna abundance and spatial distributions and the subsequent effects on vessels' trip distance. Last, it describes the model specification.

Data. Fishing location, effort, and landing data for 1991–2020 came from the Hawaii federal logbook program [58]. Federal logbook records data include date, time, and location of individual fishing sets and hauls, number of fish landed by species in an individual fishing set, number of hooks used per set, and set type (deep vs. shallow). Trip-level data recorded in the logbook include vessel information, permit status, departure and return date, and departure and return port. To focus on the relationships between trip distance and climate change and variability for the main fishing port of the Hawaii deep-set longline fishery, only deep-set trips that departed from, and returned to, the Honolulu port are included in this study. The final dataset includes 31,921 fishing trips, representing 96% of total deep-set trips (33,137 trips) between 1991 and 2020.

Trip distance is defined as the sum of the distance from the departure port to the first fishing set and haul locations (average of begin set, end set, begin haul, and end haul locations), the distances between all individual fishing set and haul locations, and the distance from the last fishing set and haul locations to the returning port. Travel distance was calculated using the geosphere package [59] in R Version 1.2.5033 [60].

SST data came from NOAA OceanWatch, CoralTemp, v3.1 [61]. To calculate the monthly SST for the whole Hawaii deep-set longline fishing ground (0˚ to 40˚N and 180˚ to 120˚W), monthly SST was obtained for each 0.05 x 0.05 pixel for the whole fishing ground and averaged over the entire area. Oceanic Niño Index (ONI), which is calculated by the NOAA National Weather Service, Climate Prediction Center, is used to examine the relationships between ENSO events and trip distance. It represents a 3-month running mean of anomalies in the SST (Extended Reconstructed Sea Surface Temperature, ERSST.v5 SST) from the average SST in 1991–2020 in the Niño 3.4 region (120˚W– 170˚W, 5˚N– 5˚S). When ONI is greater (lower) than the threshold of +/-0.5 for five consecutive months, it is classified as an El Niño (La Niña) episode.

Annual trip distance and SST. The annual average trip distance has increased over the 30-year period (1991–2020) (Fig 2). Trip distance underwent a rapid increase in 1993, 1994, and 1997, with some fluctuations between 1998 and 2005, and another rapid increasing trend after 2005, until reaching a maximum in 2010, then experienced a steady decline in the 2010s. Fig 2 also displays two SSTs: average annual SST for haul locations, and average annual SST for the whole fishing ground of the Hawaii deep-set longline fleet. The average annual SST for haul locations was calculated using the daily SST that matched the begin haul location of an individual set in a fishing trip at 5 km resolution, and then averaged across all the matching daily SSTs in a year to calculate the average annual SST for all haul locations. The average annual SST for the whole fishing ground was calculated using the monthly SST for the whole Hawaii deep-set longline fishing ground (0˚ to 40˚N and 180˚ to 120˚W) at 5 km resolution, and averaged over a year. The SST for matching haul location showed a slight decreasing trend as the Hawaii longline fleet has expanded fishing location to higher latitudes and further east into cooler waters. The SST for the whole fishing ground experienced a slight increasing trend, especially after the strong La Niña episode started in mid-1998.

Monthly trip distance and ONI. The monthly trip distance has a seasonal component (i.e. shorter trips in winter and longer trips in summer) and it shows an increasing trend over time (Fig 3). When comparing the monthly trip distance with ONI, the monthly trip distance was seasonally adjusted and detrended (Fig 4). Smaller deviations of trip distance from the

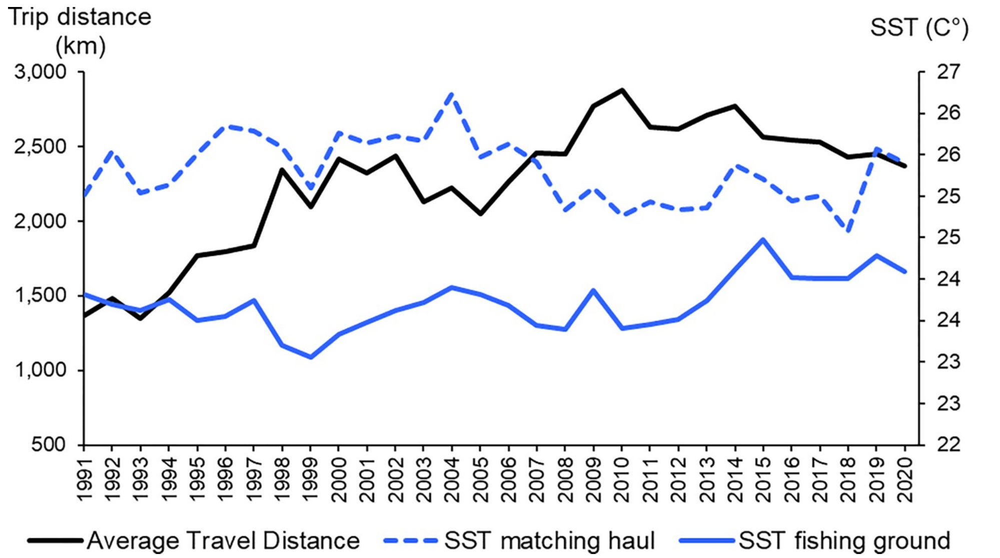

Fig 2. Annual trip distance and SST for haul location and fishing grounds, 1991–2020.

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seasonally adjusted trend was observed during ENSO events (ONI≤-0.5 or ONI≥0.5), especially during strong ENSO events (large ONI in absolute value).

Annual effort-weighted mean fishing location and SST. As trip distance was generally increasing over time, it is unknown whether fishing trips were shifting to a specific direction in relation to climate factors. Annual effort-weighted mean location (latitude, longitude) was calculated using the begin haul location (latitude, longitude) of an individual fishing set, multiplied by the number of hooks set, aggregated over a year, and divided by the annual hooks set. The scatter plot between the 5-year running mean SST of fishing grounds and weighted latitudes showed an increasing trend (slope = 4.21, *p-value* < 0.01, $R^2 = 0.29$); indicating the

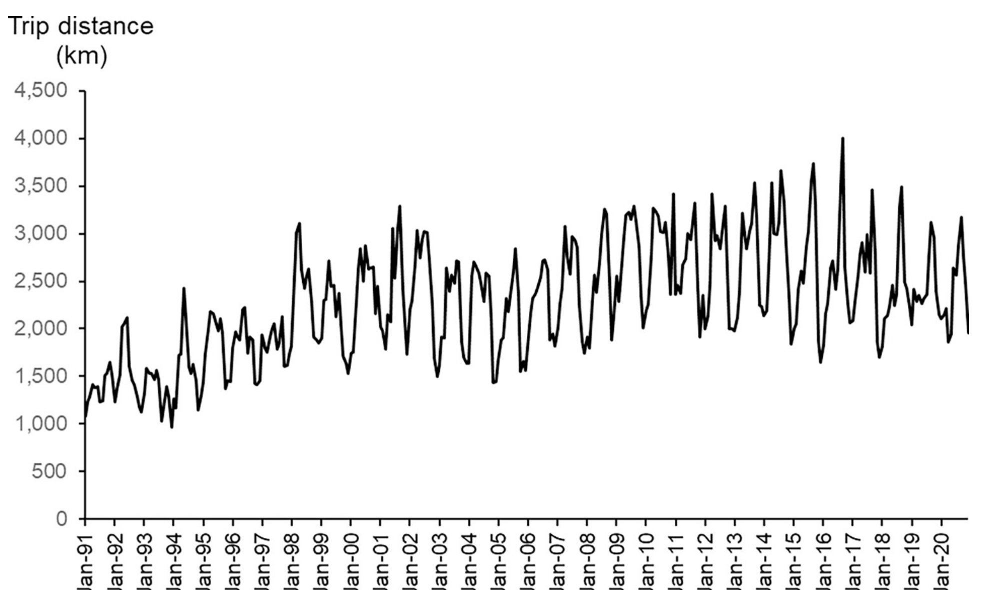

Fig 3. Monthly trip distance, 1991–2020.

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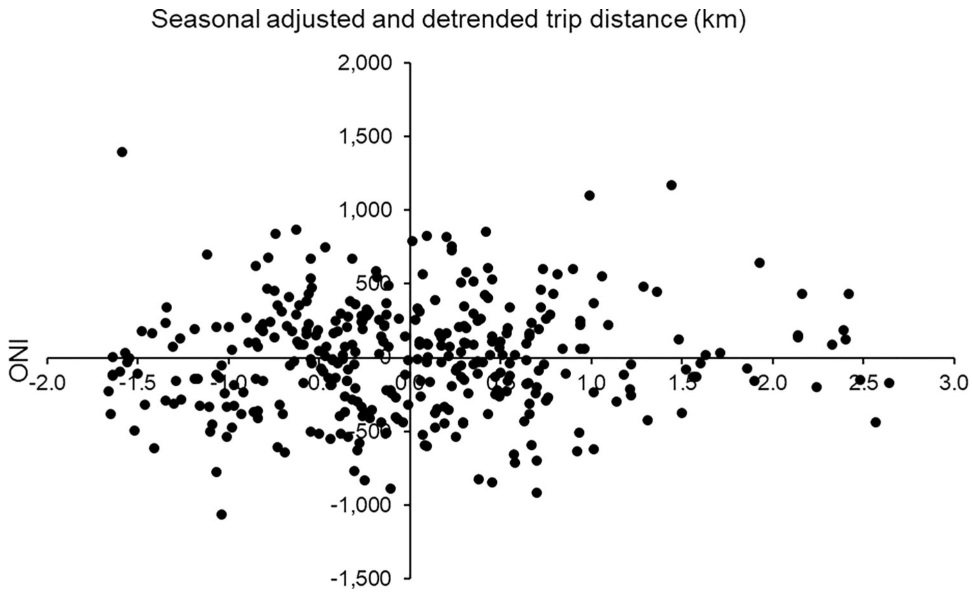

Fig 4. Seasonally adjusted and detrended monthly trip distance and ONI, 1992–2020.

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higher the SST of the fishing grounds of the Hawaii longline fleet, the higher the latitude in which the Hawaii longline vessels operated (Fig 5). The scatter plot between the 5-year running mean SST of fishing grounds and weighted longitude showed a decreasing trend (slope = -5.69, *p-value* < 0.01, $R^2 = 0.46$); indicating the higher the SST of the fishing grounds, the more eastward in which the Hawaii longline vessels operated (Fig 6).

Monthly effort-weighted mean fishing location and ONI. Similar to the monthly trip distance, the monthly effort-weighted mean latitude and longitude were seasonally adjusted and detrended when compared to the ONI in Figs 7 and 8, respectively. After the fishing

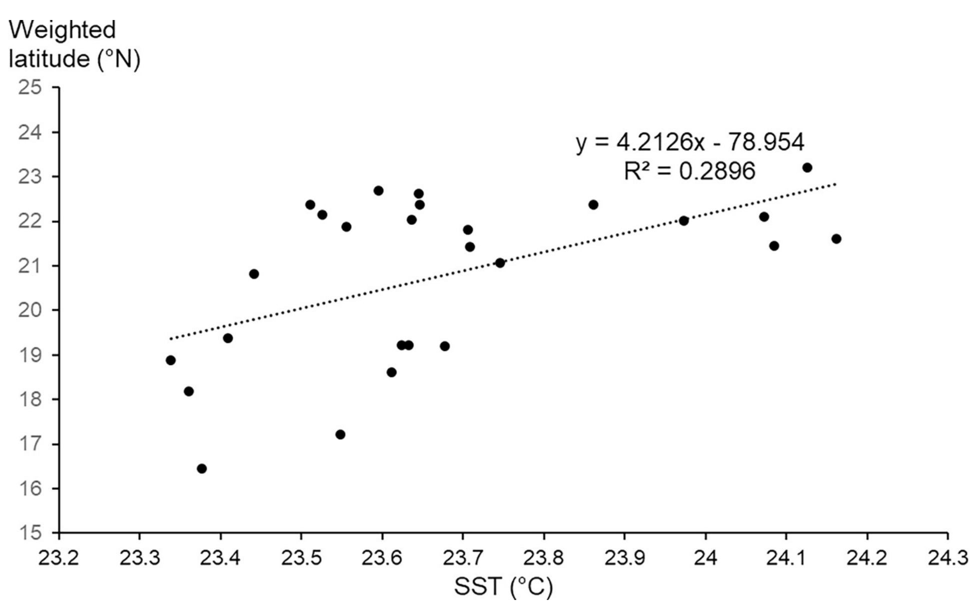

Fig 5. Annual effort-weighted mean haul latitude and 5-year running mean SST for fishing grounds, 1995–2020.

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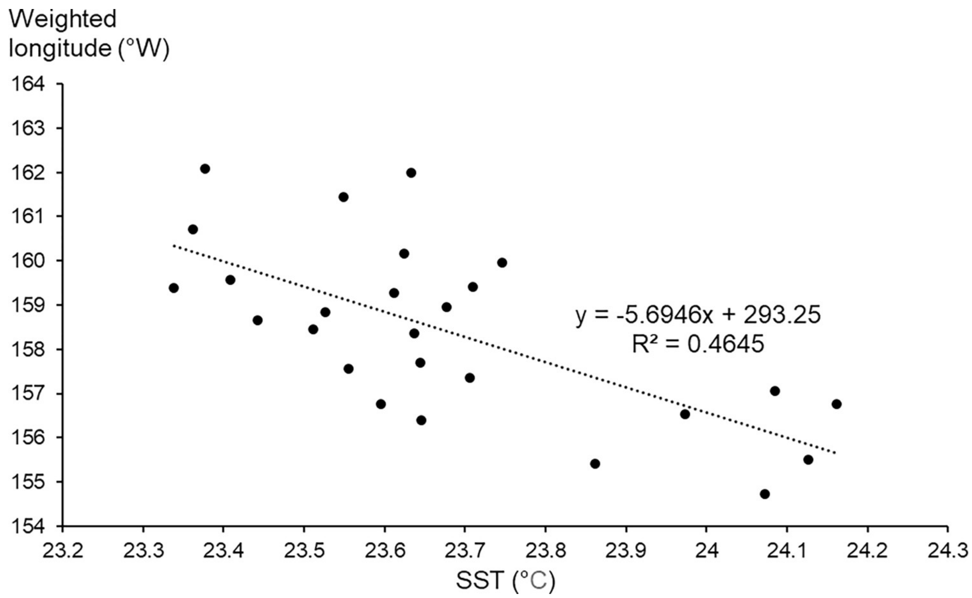

Fig 6. Annual effort-weighted mean haul longitude and 5-year running mean SST for fishing grounds, 1995–2020.

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locations were seasonally adjusted and detrended, smaller deviations of weighted latitude and longitude from the seasonally adjusted trend were observed during ENSO events (ONI$\leq$-0.5 or ONI$\geq$0.5), especially during strong ENSO events (large ONI in absolute value).

Annual trip CPUE and SST. CPUE is one of the main drivers of commercial fishers' decisions regarding distribution of fishing effort [23–25, 27]. The annual average trip CPUE for deep-set trips showed a decreasing trend, the opposite of the SST trend for the whole fishing grounds (Fig 9). Trip-level CPUE (per 1,000 hooks) was calculated as the number of fish landed in a trip divided by the number of hooks set in a trip, multiplied by 1,000 for all species

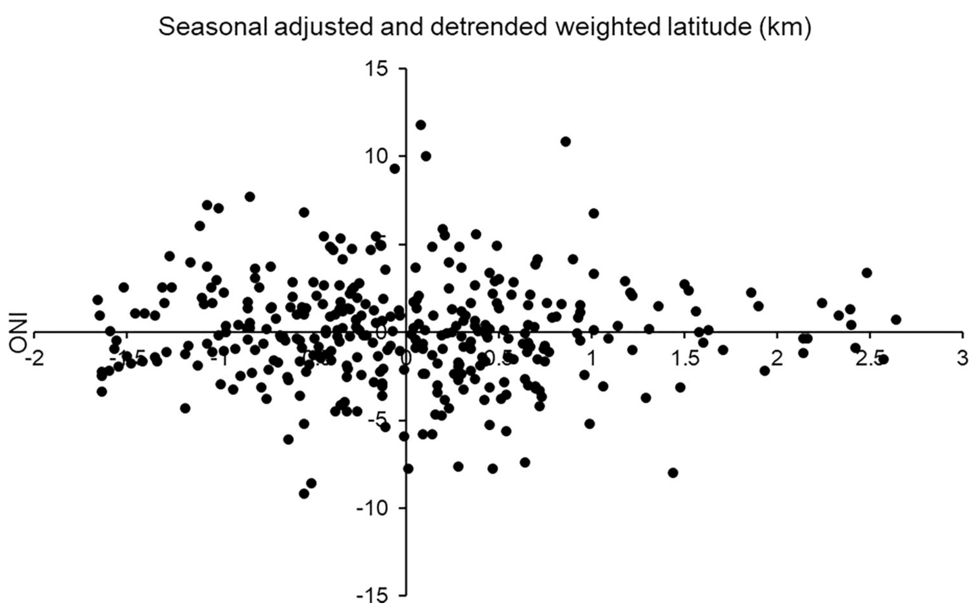

Fig 7. Seasonally adjusted and detrended monthly effort-weighted mean haul latitude and ONI, 1992–2020.

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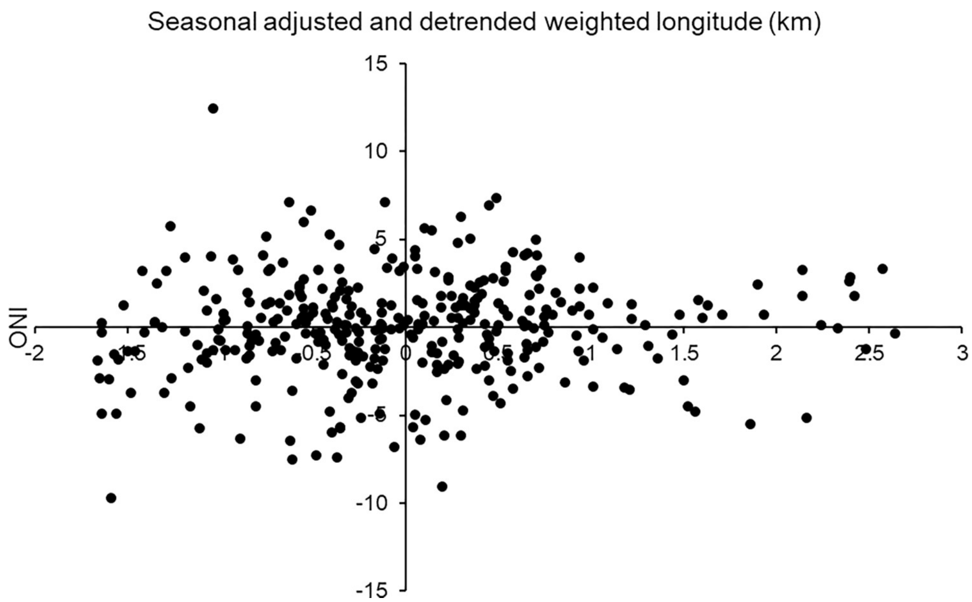

Fig 8. Seasonally adjusted and detrended monthly effort-weighted mean haul longitude and ONI, 1992–2020.

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landed. The scatter plot between the 5-year running mean SST of the whole fishing grounds and 5-year running mean annual trip CPUE showed a decreasing trend (slope = -5.63, *p-value* < 0.01, $R^2 = 0.27$), indicating the higher the SST in the fishing grounds, the lower the trip CPUE (Fig 10). Rising SST could lower CPUE for the Hawaii longline fishery as 1) higher temperatures would affect the production of phytoplankton and zooplankton on which larval and juvenile tuna feed, thereby influencing the survival of larval and juvenile tuna [6]; 2) the size of the phytoplankton was a proxy for food quality for larval and juvenile bigeye, and it was a predictor of bigeye tuna catch rates with a four-year lag for the Hawaii deep-set longline fishery

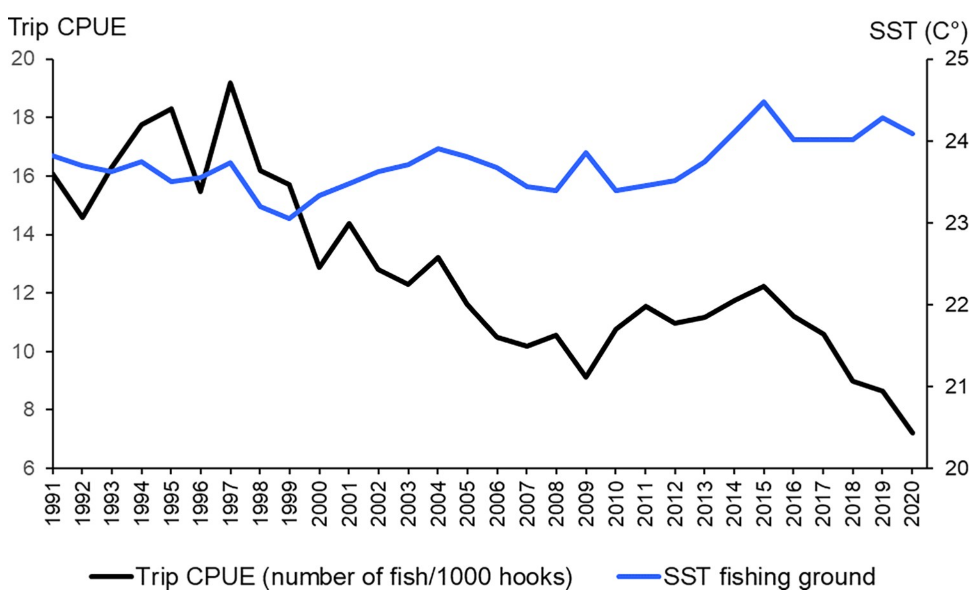

Fig 9. Annual trip CPUE and SST for fishing grounds, 1991–2020.

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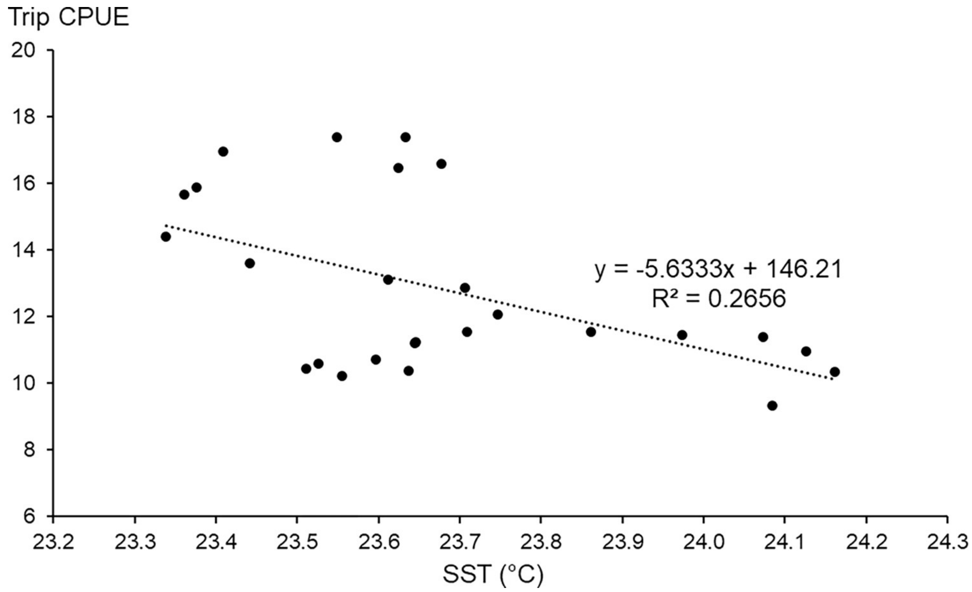

Fig 10. Five-year running mean annual trip CPUE and 5-year running mean SST for fishing grounds, 1995–2020.

https://doi.org/10.1371/journal.pclm.0000143.g010

[62]. Porreca [63] also found a significant relationship between SST and fishing yield in the WCPO.

Quarterly trip CPUE and ONI. Trip CPUE exhibited seasonal patterns, with higher trip CPUE in the first and fourth quarters, and lower trip CPUE in the third quarter. Therefore, when comparing the quarterly CPUE with ONI, the quarterly CPUE was seasonally adjusted. Figs 11–13 show the ONI and the seasonally adjusted quarterly trip CPUE for bigeye, yellowfin, and albacore (the top three species landed), respectively. Some patterns observed in Fig 11 include bigeye CPUE and ONI moving the same directions during El Niño events in 1994/95,

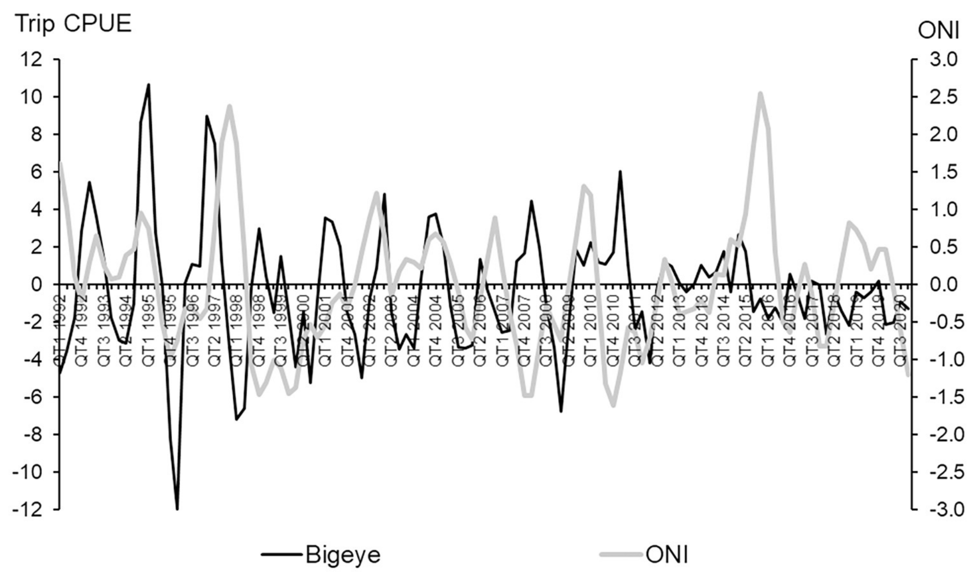

Fig 11. Seasonally adjusted quarterly trip CPUE of bigeye and ONI, 1992–2020.

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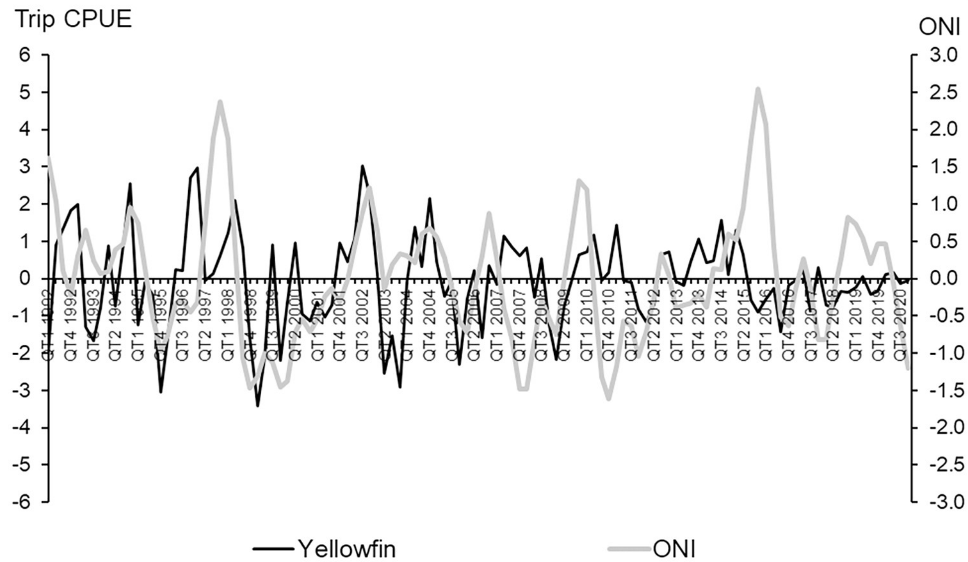

Fig 12. Seasonally adjusted quarterly trip CPUE of yellowfin and ONI, 1992–2020.

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2002, 2004, 2009/10 and La Niña events in 1995/96, 2011. In Fig 12, yellowfin and ONI moved in opposite directions during El Niño events in 1992, 1997/98, 2015/16, and La Niña events in 2007/08 and 2010/11. Albacore and ONI also moved in opposite directions during El Niño events in 1992, 1994, 1997/98, 2002, 2006, 2019, and La Niña conditions in 1998–2000, 2007, 2010/11 (Fig 13).

To examine the correlations between ENSO events and CPUE in a trip statistically, Pearson correlations between the trip-level CPUE for different tuna/non-tuna species and El Niño and La Niña conditions during the trip (here defined as 1 when ONI≥0.5 for El Niño condition or

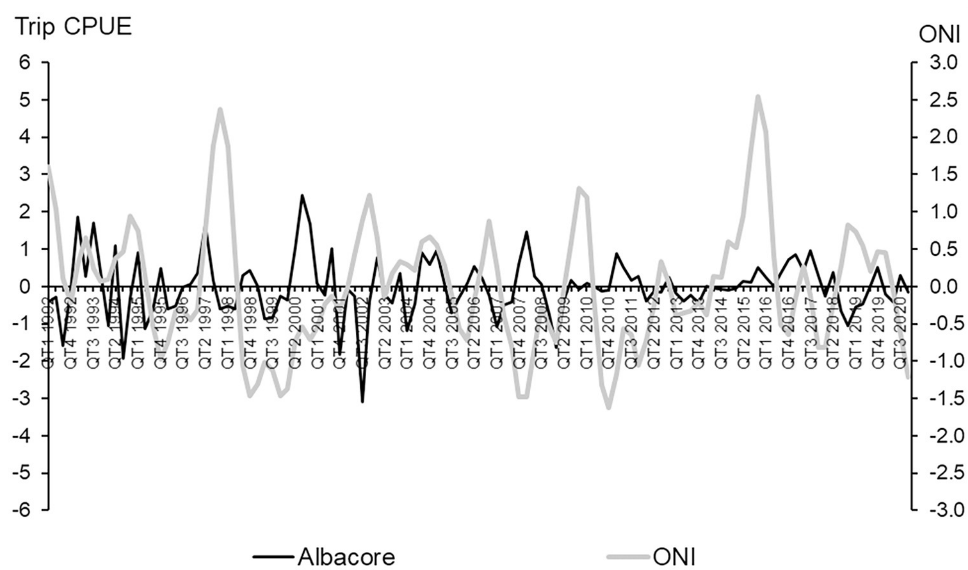

Fig 13. Seasonally adjusted quarterly trip CPUE of albacore and ONI, 1992–2020.

https://doi.org/10.1371/journal.pclm.0000143.g013

Table 1. Pearson correlation between trip-level CPUE by species and ENSO periods, 1991–2020, 1991–2001, and 2002–2020.

	1991–2020 when ONI≥0.5 (El Niño)	1991–2020 when ONI≤-0.5 (La Niña)	1991–2001 when ONI≥0.5 (El Niño)	1991–2001 when ONI≤-0.5 (La Niña)	2002–2020 when ONI≥0.5 (El Niño)	2002–2020 when ONI≤-0.50 (La Niña)
Trip CPUE for bigeye	0.119**	-0.011	0.093**	-0.048**	0.152**	-0.002
Trip CPUE for yellowfin	-0.016**	0.069**	-0.030*	-0.001	-0.006	0.099**
Trip CPUE for albacore	-0.019**	0.050**	-0.012	-0.016	-0.013	0.013
Trip CPUE for skipjack	0.124**	-0.065**	0.240**	-0.130**	0.107**	-0.075**
Trip CPUE for non-tuna	0.034**	-0.039**	0.099**	-0.157**	0.014*	-0.007
Trip CPUE for all species	0.086**	0.004	0.010**	-0.098**	0.010**	0.010

Note

** significant at the 1% level (2-tailed)

* significant at the 5% level (2-tailed).

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0 otherwise, and 1 when ONI≤-0.5 for La Niña condition or 0 otherwise) were conducted (Table 1). Pearson correlations were examined for the whole study period and two sub-periods (1991–2001 and 2002–2020); because the deep-set longline fishery started to increase with higher fishing effort and landings with the closure of the shallow-set longline fishery between 2001 and 2004, and the spatial distribution of the Hawaii deep-set longline fishery started to expand further from the port in 2002 (Fig 1). Trip-level CPUE for bigeye, skipjack, and non-tuna species was positively correlated with El Niño conditions (significant for overall and two sub-periods) and negatively correlated with La Niña conditions (significant for skipjack and non-tuna). The negative correlation between trip-level CPUE for bigeye and La Niña was significant for 1991–2001 only. Relative to bigeye, opposite and significant correlations were observed for yellowfin and albacore for the whole study period and during some sub-periods. Correlation between CPUE for all species and ENSO periods followed the same patterns as the bigeye which represents the highest proportion of catches in a trip.

Model. This study uses a regression model to examine the effects of climate change and variability on fishing trip distance, following a similar approach to Haynie & Pfeiffer [23]. They used cold pool size as the climate factor, whereas this study includes two climate variables that might affect trip distance in the model specification. The first one, monthly SST for the entire fishing ground of the Hawaii deep-set longline fishery, can estimate how changes in SST over time in the whole fishing ground could affect trip distance. The sector factor, ONI index, is included to examine how ENSO events could affect trip distance, as different tuna species respond differently to ENSO events. The advantage of using ONI as a continuous variable is its ability to capture the effect of variation in ONI on trip distance; a more severe ENSO event might have a greater effect on trip distance. Because CPUE for different tuna species had opposite effects during El Niño and La Niña conditions, ONI is modeled as a quadratic relationship with trip distance.

In Haynie & Pfeiffer [23], biological, regulatory, trip specific, and vessel specific factors that potentially could affect trip distance are also considered in the model specification. The final model specification (i.e., what specific variables to include in the model) is determined based on the lowest Akaike Information Criterion (AIC), root mean squared error (RMSE), and mean absolute error (MAE). In addition to the two climate factors, the final model for empirical estimation includes fish abundance, diesel price, fisheries policies that restrict area access, unique vessel characteristics, and annual variations.

The higher the fish abundance, the shorter the trip required to find the target species. Hawaii longline deep-set fishery's fishing effort exhibited distinct quarterly spatial movement

[40] and seasonal differences in catch rates of different species [39], therefore, quarterly biomass is included in the model. Because bigeye tuna abundance is unknown on a quarterly basis, it is represented by the effort-adjusted aggregate bigeye landings of the entire deep-set fleet in a quarter. It was calculated as the total bigeye landings in all deep-set trips in a quarter divided by the total hooks used in all deep-set trips in that quarter, multiplied by 1,000 (for unit per 1,000 hooks). Quarterly non-bigeye biomass was calculated in a similar way for non-bigeye species. These variables can capture seasonal variations in stock, migratory patterns, and abundances that affect CPUE. This calculation of biomass followed the same method as Peña-Torres et al. [25] who used the effort-adjusted aggregate monthly jack mackerel landings of the entire Chilean straddling pelagic fleet as a proxy for the monthly biomass and included it as a covariate to estimate the impact of El Niño events on fishing location choice. Inflation adjusted diesel price is used to identify how it influenced trip distance as fuel cost is the most important trip cost item in the Hawaii longline fishery [38]. Other factors include spatial restriction policies that affected distance for trips taken during the periods when closures were in place in the WCPO and EPO, conditions that were unique in a particular year and affected all vessels equally, and covariates that are unique to individual vessels. Vessel specific variables capture individual vessels' unique features like size, gross tonnage, and fuel efficiency. These features affect the distance travel capability, hold capacity, and distance traveled. Vessel specific variables can also capture fisher experience, knowledge, and skills that could influence trip distance. Vessel specific fixed effects are modeled as dummy variables for individual vessels.

In addition to using distance per trip as the dependent variable, another model used trip distance per fish per trip as the dependent variable which is defined as the trip distance divided by the number of fish kept per trip. This can be considered the average cost of travel [23]. For example, if landings increase proportionally with trip distance, distance per fish is constant. Likewise, if landings increase at a higher rate than trip distance, distance per fish decreases.

Due to the non-normal distribution of trip distance, a generalized linear model (GLM) using gamma distribution with log link model and vessel fixed effects is estimated to address the potential heteroscedasticity in the error term. The functional form to estimate vessel trip distance is specified as:

$$\begin{aligned} f(Y_{ij}) = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{SST}_m + \boldsymbol{\beta}_2 \boldsymbol{ENSO}_m{}^2 + \boldsymbol{\beta}_3 \boldsymbol{DIESEL}_m + \boldsymbol{\beta}_4 \boldsymbol{BIOMASS}_{big,q} + \boldsymbol{\beta}_5 \boldsymbol{BIOMASS}_{non-big,q} \\ + \boldsymbol{\beta}_6 \boldsymbol{C1}_{ij} + \boldsymbol{\beta}_7 \boldsymbol{C2}_{ij} + \boldsymbol{\beta}_{8y} \boldsymbol{E}_y + \boldsymbol{\beta}_{9i} \boldsymbol{V}_i + \boldsymbol{\varepsilon}_{ij}. (1) \end{aligned}$$

where *i* stands for individual vessel, *j* stands for individual fishing trip, *m* stands for month, *q* stands for quarter, *y* stands for year.

- Y_{ij} is trip distance or trip distance per fish for individual vessel *i* in trip *j*.
- SST_m is monthly sea surface temperature for the entire fishing ground.
- $ENSO_m{}^2$ is the square of ONI.
- $DIESEL_m$ is inflation adjusted monthly diesel price.
- $BIOMASS_{big,q}$ is the effort-adjusted aggregate bigeye landings of the entire deep-set fleet in a quarter.
- $BIOMASS_{non\text{-}big,q}$ is the effort-adjusted aggregate non-bigeye landings of the entire deep-set fleet in a quarter.
- $C1_{ij}$ and $C2_{ij}$ take the value of one when bigeye tuna closures were in effect that impacted vessel *i* in trip *j* (based on vessel's dual permit status and size), and 0 otherwise.

- ○ $C1_{ij} = 1$ represents closure in WCPO
- ○ $C2_{ij} = 1$ represents closure in EPO.
- E_y are year dummy variables.
- V_i are individual vessel specific fixed effects.

The model was run in the R statistical programming language, version 3.1.2 [60]. Multicollinearity of covariates was checked using variance inflation factor (VIF). VIF values for all covariates (excluding year and vessel specific fixed effects) in the estimated model were less than 2, indicating no multicollinearity. In order to control for serial correlation and heteroscedastic errors at the vessel level, clustered standard errors at the vessel level were used. Testing of clustered standard errors were conducted using lmtest package in R [64].

Results

Table 2 shows the model results, with distance per trip and distance per fish as the dependent variables. All coefficients were significant, with the exception of diesel price on distance per fish. The positive coefficient for SST means the higher the SST of the fishing grounds of the Hawaii longline fleet, the longer the trip distance and distance per fish. The coefficient for ONI^2 is negative, representing shorter trip distance with El Niño and La Niña conditions. The coefficients of other variables had the expected sign. The greater the bigeye biomass and non-bigeye biomass, the shorter the trip distance and distance per fish, as it is easier to catch a fish with greater biomass that requires less travel. Diesel price has a negative correlation with trip distance but insignificant correlation with distance per fish, indicating the higher diesel price, the shorter the trip distance, likely due to higher trip costs. However, an increase in diesel price does not affect the average trip distance per fish. This is possible if longer travel distance is compensated for more landings proportionally. Closures in the WCPO compel vessels to

Table 2. Estimated coefficients from the model estimation.

	Dependent variable = Trip distance	Dependent variable = Distance per fish
SST fishing ground	0.0414** (0.0031)	0.0294** (0.0069)
ONI^2	-0.0496** (0.0028)	-0.0483** (0.0087)
Diesel	-0.0208* (0.0088)	-0.0113 (0.0261)
Biomass of bigeye	-0.0591** (0.0034)	-0.1434** (0.0094)
Biomass of non-bigeye	-0.0055** (0.0017)	-0.0661** (0.0084)
Closures in WCPO	0.3708** (0.0162)	0.3877** (0.0539)
Closures in EPO	-0.1801** (0.0257)	-0.2655** (0.0434)
Constant	6.7799** (0.0953)	10.6416** (0.1953)
Year effects	Included	Included
Vessel fixed effects	Included	Included
Observations (number of trips)	31,918	31,912
R^2	0.37	0.27
AIC	516,864	639,925
RMSE	836	15,825
MAE	645	5,589

Note: Numbers in parentheses are clustered standard error at vessel level.

$^{*}\ p < 0.05$

$^{**}p < 0.01$.

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Table 3. Estimated trip distance effect (ratio by which trip distance is changed) based on coefficients from model estimation.

	Dependent variable = Trip distance	Dependent variable = Distance per fish
SST fishing ground	1.042**	1.030**
ONI = 1/-1	0.952**	0.953**
ONI = 2/-2	0.820**	0.824**
ONI = 3/-3	0.640**	0.648**
Diesel	0.979*	0.989
Biomass of bigeye	0.943**	0.866**
Biomass of non-bigeye	0.994**	0.936**
Closures in WCPO	1.449**	1.474**
Closures in EPO	0.835**	0.767**

Note

* $p<0.05$

** $p<0.01$.

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travel further to the EPO, whereas closures in the EPO constrain vessels to stay in the WCPO, and therefore, shorten the travel distance for vessels which would otherwise go to the EPO if it were opened. Because the regression is gamma with log link, coefficients in Table 2 are converted by exponentiation to acquire the ratio by which trip distance is multiplied due to the change of a unit of independent variable (Table 3).

When the dependent variable is trip distance, a one degree increase in SST is associated with 4.2% increase in trip distance (100 km, by using the mean travel distance = 2,356 km). An increase in ONI from 0 to 1 corresponds to a 5.0% (114 km) decrease in trip distance. Because of the quadratic relationship with trip distance, the larger the absolute value of ONI, the larger the decrease in trip distance. Compared with climate factors, fishery closures have larger effects on trip distance. WCPO closures induce longer trip distance (44.9%) (1,058 km), and EPO closures induce shorter trip distance (17.0%) (388 km). As expected, the higher the bigeye biomass (number of fish per 1,000 hooks), the shorter the trip distance (5.7%) (135 km). To a lesser extent, the larger the non-bigeye biomass, the shorter the trip distance (0.6%) (13 km). An increase in diesel price by a dollar induces a 2.1% (49 km) decrease in trip distance.

When treating distance per fish as the dependent variable instead of trip distance, SST and ENSO events have similar effects. Biomass has larger negative effects (~6%–8% more) on distance per fish, indicating efficiency gain from greater biomass.

Conclusion and suggestion

This study used 30 years of fishery-dependent data and environmental variables to quantify the relationships between trip distance of the Hawaii longline fleet and climate factors. The model results indicate that vessel trip distance was correlated with SST and ENSO events, possibly through their influence on the spatial distributions of tunas and the subsequent effects on catch rates. However, the effects from changes in SST and ENSO events were opposite. The positive relationship of trip distance with SST indicates that the rising SST of Hawaii longline fishing grounds over the study period was associated with longer trip distance. This could be due to the opposite correlation between SST and trip CPUE, and a lower CPUE could induce longer trip distance as more time is required to search for target species. The Hawaii longline fleet's fishing location has shifted toward higher latitude and eastward from the Honolulu fishing port. This is consistent with the poleward shift in tuna habitat that occurred in the North Pacific Ocean during the period of warming ocean [17] and the increasing trend of longline catches of tropical tuna in subtropical areas of the western Pacific Ocean over the past four decades [11]. The negative relationship of trip distance with ENSO events suggests that the Hawaii longline fleet took advantage of the changes in spatial distributions of different tuna species during ENSO events, and utilized its locational advantage to travel in different directions in the Pacific Ocean to achieve higher CPUE that occurred closer to the Honolulu port, thereby shortening its travel distance. Several empirical studies supported higher tuna CPUE/ recruitment during ENSO events in the same fishing grounds of the Hawaii longline fleet. These include bigeye habitat hotspots developed north of the Hawaiian Islands during El Niño events [47]; above (below) average bigeye recruitments coincided with strong El Niño (La Niña) events in the EPO [65], an area where the Hawaii longline fleet was likely to operate in the third quarter of the year [40]; and higher yellowfin hook rates observed during La Niña events by tuna longliners in the same area where Hawaii longline fleet operated due to a northward expansion of yellowfin's preferred habitat [21]. These past findings were consistent with the correlations of Hawaii longline CPUE during ENSO events (higher bigeye CPUE during El Niño events and higher yellowfin CPUE during La Niña events). The observations of Hawaii longline fleet fishing closer to the Honolulu port during ENSO events (Figs 7 and 8) suggest that the Hawaii longline fleet was able to achieve higher CPUE with shorter travel distance during ENSO events.

It is important to note that although the model result predicts an increase in trip distance with rising ocean temperatures, the future effect is expected to be small, as it takes a long time for ocean temperature to increase by one degree. Projections showed that SST in the WCPO will increase by 2.5˚C to 3.5˚C by 2100 under the "business-as-usual" greenhouse gas emissions RCP8.5 scenario [66]. Therefore, higher SST can be considered a long-term impact on the fishery. On the other hand, ENSO events could happen in any year and will probably be more frequent [67] and more extreme in the future [68], leading to greater influence on trip distance. The model results show non-climate factors such as fisheries management policies, biomass, and diesel price also affected trip distance. Particularly, area closures that affected access, and bigeye biomass that influenced the ease of finding fish, had larger effects on trip distance when compared to climate factors. This is similar to the findings in Haynie & Pfeiffer [23] that trends in climate had a relatively low impact on the spatial distribution of fishing effort.

Some studies included the lagged effects of climate impacts on fishing location [22, 23, 25, 26], but they are omitted in this study. These effects are complex and difficult to identify as climate change could affect spawning grounds, larval survival, biomass, and recruitment, and some impacts could take years to realize [24]. Peña-Torres et al. [25] pointed out that the ONI index could be viewed as an autoregressive process, and inconsistent model estimates might arise when including the contemporaneous ONI and its lags in the model. Since no study has identified the lagged effects of ENSO events on the longline fisheries targeting bigeye tuna, this study only used the contemporaneous ONI index.

The estimated changes in travel distance can be linked with the trip cost model in Chan & Pan [69] to determine the changes in trip costs due to climate change and variability. Chan & Pan's [69] model used trip specific variables including distance and other vessel specific variables to predict fishing trip costs for the Hawaii longline fishery. Using the estimated trip cost model for the Hawaii longline fishery (gamma with log link) and the mean trip distance (2,356 km), Table 4 shows the estimated trip cost impacts due to changes in trip distance (from Table 2). SST changes have relatively low impacts on trip costs (~1%); ENSO events have larger (~1% to 9%) effects on trip costs.

With the significant relationships between climate factors and trip distance found in this study combined with the projected increase in ocean temperature and the poleward and

Table 4. Estimated trip cost impacts based on trip distance model in this study and trip cost model in Chan & Pan [69].

	Estimated percentage change in trip costs
SST fishing ground	1.1%
ONI = 1/-1	-1.3%
ONI = 2/-2	-4.7%
ONI = 3/-3	-9.3%
Diesel	-0.5%
Biomass of bigeye	-1.5%
Biomass of non-bigeye	-0.1%
Closures in WCPO	11.9%
Closures in EPO	-4.3%

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eastward shifts in bigeye tuna in the future [14], it is anticipated that trip distance will extend further east of Honolulu in the future. Instead of landing the catches in Hawaii, it could become more economical for vessels to land their catches on the mainland west coast. Prior to 2010, fewer than 10 trips unloaded their landings in the west coast, but that number has increased to around 80 per year recently (5% of total trips in a year). This trend could be the result of climate change shifting the spatial distribution of bigeye tuna further away from Hawaii. If SST continues to increase, this could lead to lower supply of wild caught fresh pelagic fish in Hawaii. Consumption of seafood is culturally important in Hawaii. The annual average seafood consumption in Hawaii is 37 lb per person (including non-commercial catch from 2000 to 2009) [70], which is consistently higher than the national average (<20 lb) [42]. The findings in this study provide information to fisheries managers when considering the management actions related to the potential effect of climate change on fresh seafood supply to the island economy.

Climate change will continue to impact the ecosystem structure of the ocean. Increasing ocean temperature is expected to persist into the future and affect fish biomass and spatial distribution. The maximum catch potential around the Hawaii EEZ was projected to decrease by 15%–30% by 2100 under the RCP8.5 scenario [3]. Tuna biomass and distribution are expected to adjust as tunas are highly mobile species that follow productive areas. Tuna distribution models projected bigeye tuna to shift poleward by the end of the century [17]. Bigeye biomass in the WCPO is projected to decline by the end of the century due to unfavorable spawning and feeding habitat including higher SST, less food, and decreased dissolved oxygen concentration in sub-surface waters [7]. On the other hand, bigeye biomass in the EPO is projected to increase as SST in the EPO will become optimal for bigeye spawning by 2100. Additionally, the habitat for adult bigeye will improve due to higher dissolved oxygen concentration allowing adult bigeye to travel to a deeper forage layer [6, 7]. However, not the entire EPO is expected to be a better environment for bigeye, as the oxygen minimum zone in the tropical EPO is projected to expand, limiting their habitat in this area [40]. ENSO events are projected to occur more frequently under some global climate change scenarios [67, 68] and their intensity may increase as well [71]. As a result, it is expected that commercial fishing fleets will continue to change their fishing locations. New records of ocean temperatures and more frequent and severe ENSO events could happen in the future. It is unknown whether the future climate scenarios will severely affect the survival rates of tuna larvae and change their spawning grounds dramatically. Nevertheless, this reduced form of estimation of climate change and climate variability on trip distance provides baseline information to include fisher behavior in light of climate change and variability. Better understanding fisher behavior can support future ecosystem modeling of the climate change impacts on fisheries and fisheries management related to climate-driven changes of marine ecosystems.

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References

1. Bell JD, Senina I, Adams T, Aumont O, Calmettes B, Clark S, et al. Pathways to sustaining tuna-dependent Pacific Island economies during climate change. Nat Sustain. 2021; 4:900–10. https://doi.org/10.1038/s41893-021-00745-z
2. Criddle KR, Herrmann M, Greenberg JA, Feller EM. Climate fluctuation and revenue maximization in the eastern Bering Sea fishery for walleye pollock. North Am J Fish Manag. 1998; 18(1):1–10. https://doi.org/10.1577/1548-8675(1998)018%3C0001:cfarmi%3E2.0.co;2
3. Lam VWY, Allison EH, Bell JD, Blythe J, Cheung WWL, Frölicher TL, et al. Climate change, tropical fisheries and prospects for sustainable development. Nat Rev Earth Environ. 2020; 1:440–54. http://dx.doi.org/10.1038/s43017-020-0071-9
4. Lehodey P, Senina I, Nicol S, Hampton J. Modelling the impact of climate change on South Pacific albacore tuna. Deep Res Part II Top Stud Oceanogr. 2015; 113:246–59. https://doi.org/10.1016/j.dsr2.2014.10.028
5. Lehodey P, Senina I, Titaud O, Calmettes B, Nicol S, Hampton J, et al. Project 62: SEAPODYM applications in WCPO. In: 9th regular session of the scientific committee, Western and Central Pacific Fisheries Commission, 6–14 August 2013. Pohnpe, Federated States of Micronesia; 2013. p. 1–63. http://www.wcpfc.int/meetings/2013/9th-regular-session-scientific-committee
6. Lehodey P, Hampton J, Brill RW, Nicol S, Senina I, Calmettes B, et al. Chapter 8, Vulnerability of tropical Pacific fisheries and aquaculture to climate change. In: Vulnerability of oceanic fisheries in the tropical Pacific to climate change. Secretariat of the Pacific Community; 2011. p. 433–92.
7. Lehodey P, Senina I, Sibert J, Bopp L, Calmettes B, Hampton J, et al. Preliminary forecasts of Pacific bigeye tuna population trends under the A2 IPCC scenario. Prog Oceanogr. 2010; 86(1–2):302–15. http://dx.doi.org/10.1016/j.pocean.2010.04.021
8. Peña-Torres J, Agostini C, Vergara S. Fish stock endogeneity in a harvest function: "El Niño" effects on the Chilean jack mackerel fishery. Rev Análisis Económico. 2007; 22(2):75–99. https://www.rae-ear.org/index.php/rae/article/view/73
9. Senina I, Lehodey P, Smith N, Hampton J, Reid C, Bell J, et al. Impact of climate change on tropical Pacific tuna and their fisheries in Pacific Islands waters and high seas areas. Final Report (CI-3) for SAN 6003922. 2018. https://www.semanticscholar.org/paper/Impact-of-climate-change-on-tropical-tuna-species/f7adad51b675f8e8e6492681b4c99e83de4cf1b8
10. Woodworth-Jefcoats PA, Blanchard JL, Drazen JC. Relative impacts of simultaneous stressors on a pelagic marine ecosystem. Front Mar Sci. 2019; 6:383. https://doi.org/10.3389/fmars.2019.00383

11. Monllor-Hurtado A, Pennino MG, Sanchez-Lizaso JL. Shift in tuna catches due to ocean warming. PLOS ONE. 2017; 12(6):1–10. https://doi.org/10.1371/journal.pone.0178196 PMID: 28591205

12. Perry IR. Potential impacts of climate change on marine wild capture fisheries: An update. J Agric Sci. 2011; 149(S1):63–75. https://doi.org/10.1017/S0021859610000961

13. Perry AL, Low PJ, Ellis JR, Reynolds JD. Climate change and distribution shifts in marine fishes. Science. 2005; 308(5730):1912–5. https://doi.org/10.1126/science.1111322 PMID: 15890845

14. Woodworth-Jefcoats PA, Polovina JJ, Drazen JC. Climate change is projected to reduce carrying capacity and redistribute species richness in North Pacific pelagic marine ecosystems. Glob Chang Biol. 2017; 23(3):1000–8. https://doi.org/10.1111/gcb.13471 PMID: 27545818

15. Cheung WWL, Watson R, Pauly D. Signature of ocean warming in global fisheries catch. Nature. 2013; 497(7449):365–8. https://doi.org/10.1038/nature12156 PMID: 23676754

16. Cheung WWL, Lam VWY, Sarmiento JL, Kearney K, Watson R, Zeller D, et al. Large-scale redistribution of maximum fisheries catch potential in the global ocean under climate change. Glob Chang Biol. 2010; 16(1):24–35. https://doi.org/10.1111/j.1365-2486.2009.01995.x

17. Erauskin-Extramiana M, Arrizabalaga H, Hobday AJ, Cabré A, Ibaibarriaga L, Arregui I, et al. Large-scale distribution of tuna species in a warming ocean. Glob Chang Biol. 2019; 25(6):2043–60. https://doi.org/10.1111/gcb.14630 PMID: 30908786

18. Lehodey P. Climate and fisheries: an insight from the Pacific Ocean. In: Stenseth N, Ottersen G, Hurrell J, Belgrano A, editors. Marine ecosystems and climate variation the North Atlantic: A comparative perspective. Oxford University Press; 2005. p. 137–46.

19. Lehodey P. Impacts of the El Niño Southern Oscillation on tuna populations and fisheries in the tropical Pacific Ocean. Noumea, New Caledonia; 2000. Report No.: SCTB13 Working Paper. https://www.spc.int/DigitalLibrary/Doc/FAME/Meetings/SCTB/13/RG_1.pdf

20. Lehodey P, Bertignac M, Hampton J, Lewis A, Picaut J. El Niño Southern Oscillation and tuna in the western Pacific. Lett to Nat. 1997; 389:715–718. https://doi.org/10.1038/39575

21. Lu H-J, Lee K-T, Lin H-L, Liao C-H. Spatio-temporal distribution of yellowfin tuna Thunnus albacares and bigeye tuna Thunnus obesus in the tropical Pacific Ocean in relation to large-scale temperature fluctuation during ENSO episodes. Fish Sci. 2001; 67(6):1046–52. https://doi.org/10.1046/j.1444-2906.2001.00360.x

22. Cimino MA, Anderson M, Schramek T, Merrifield S, Terrill EJ. Towards a fishing pressure prediction system for a western Pacific EEZ. Sci Rep. 2019; 9(461):1–10. https://doi.org/10.1038/s41598-018-36915-x PMID: 30679554

23. Haynie AC, Pfeiffer L. Climatic and economic drivers of the Bering Sea walleye pollock (Theragra chalcogramma) fishery: Implications for the future. Can J Fish Aquat Sci. 2013; 70(6):841–53. https://doi.org/10.1139/cjfas-2012-0265

24. Haynie AC, Pfeiffer L. Why economics matters for understanding the effects of climate change on fisherie. ICES J Mar Sci. 2012; 69(7):1160–7. https://doi.org/10.1093/icesjms/fss021

25. Peña-Torres J, Dresdner J, Vasquez F. El Niño and fishing location decisions: The Chilean straddling jack mackerel fishery. Mar Resour Econ. 2017; 32(3):249–75. https://doi.org/10.1086/692073

26. Sun CH, Chiang FS, Tsoa E, Chen MH. The effects of El Niño on the mackerel purse-seine fishery harvests in Taiwan: An analysis integrating the barometric readings and sea surface temperature. Ecol Econ. 2006; 56(2):268–79. https://doi.org/10.1016/j.ecolecon.2005.02.001

27. Wu Y-L, Lan K-W, Tian Y. Determining the effect of multiscale climate indices on the global yellowfin tuna (Thunnus albacares) population using a time series analysis. Deep Res Part II Top Stud Oceanogr. 2020; 175:104808. https://doi.org/10.1016/j.dsr2.2020.104808

28. Abascal FJ, Peatman T, Leroy B, Nicol S, Schaefer K, Fuller DW, et al. Spatiotemporal variability in bigeye vertical distribution in the Pacific Ocean. Fish Res. 2018; 204:371–9. https://doi.org/10.1016/j.fishres.2018.03.013

29. Mislan KAS, Deutsch CA, Brill RW, Dunne JP, Sarmiento JL. Projections of climate-driven changes in tuna vertical habitat based on species-specific differences in blood oxygen affinity. Glob Chang Biol. 2017; 23(10):4019–28. https://doi.org/10.1111/gcb.13799 PMID: 28657206

30. Howell EA, Kobayashi DR. El Niño effects in the Palmyra Atoll region: Oceanographic changes and bigeye tuna (Thunnus obesus) catch rate variability. Fish Oceanogr. 2006; 15(6):477–89. https://doi.org/10.1111/j.1365-2419.2005.00397.x

31. Lan KW, Wu YL, Chen LC, Naimullah M, Lin TH. Effects of climate change in marine ecosystems based on the spatiotemporal age structure of top predators: A case study of bigeye tuna in the Pacific Ocean. Front Mar Sci. 2021; 8:1–13. https://doi.org/10.3389/fmars.2021.614594

32. Williams P, Ruaia T. Overview of tuna fisheries in the western and central Pacific Ocean, including economic conditions– 2020. In: 17th regular session of the scientific committee, Western and Central

Pacific Fisheries Commission, 11–19 August 2021. Online meeting; 2021. p. 1–66. https://meetings.wcpfc.int/node/12527

33. Zhou W, Hu H, Fan W, Jin S. Impact of abnormal climatic events on the CPUE of yellowfin tuna fishing in the central and western Pacific. Sustainability. 2022; 14:1217. https://doi.org/10.3390/su14031217
34. Evans K, Langley A, Clear NP, Williams P, Patterson T, Sibert J, et al. Behaviour and habitat preferences of bigeye tuna (Thunnus obesus) and their influence on longline fishery catches in the western Coral Sea. Can J Fish Aquat Sci. 2008; 65(11):2427–43. https://doi.org/10.1139/F08-148
35. Lowe TE, Brill RW, Cousins KL. Blood oxygen-binding characteristics of bigeye tuna (Thunnus obesus), a high-energy-demand teleost that is tolerant of low ambient oxygen. Mar Biol. 2000; 136(6):1087–98. https://doi.org/10.1007/s002270000255
36. Schaefer KM, Fuller DW. Vertical movements, behavior, and habitat of bigeye tuna (Thunnus obesus) in the equatorial eastern Pacific Ocean, ascertained from archival tag data. Mar Biol. 2010; 157 (12):2625–42. https://doi.org/10.1007/s00227-010-1524-3
37. Rubio I, Ganzedo U, Hobday AJ, Ojea E. Southward re-distribution of tropical tuna fisheries activity can be explained by technological and management change. Fish Fish. 2020; 21:511–21. https://doi.org/10.1111/faf.12443 PMID: 32612453
38. Kalberg KO, Pan M. 2012 Economic cost earnings of pelagic longline fishing in Hawaii. U.S. Department of Commerce; NOAA Tech.; NOAA-TM-NMFS-PIFSC-56; 2016. 60 p. https://doi.org/10.7289/V5/TM-PIFSC-56
39. Gilman E, Chaloupka M, Read A, Dalzell P, Holetschek J, Curtice C. Hawaii longline tuna fishery temporal trends in standardized catch rates and length distributions and effects on pelagic and seamount ecosystems. Aquat Conserv Mar Freshw Ecosyst. 2012; 22(4):446–88. https://doi/org/10.1002/aqc.2237
40. Woodworth-Jefcoats PA, Polovina JJ, Drazen JC. Synergy among oceanographic variability, fishery expansion, and longline catch composition in the central North Pacific Ocean. Fish Bull. 2018; 116(3–4):228–39. https://doi.org/10.7755/FB.116.3-4.2
41. Ayers AL, Hospital J, Boggs C. Bigeye tuna catch limits lead to differential impacts for Hawai'i longliners. Mar Policy. 2018; 94:93–105. https://doi.org/10.1016/j.marpol.2018.04.032
42. National Marine Fisheries Service. Fisheries of the United States, 2019. U.S. Department of Commerce, NOAA Current Fishery Statistics No. 2019. 2021. https://www.fisheries.noaa.gov/national/sustainable-fisheries/%0Afisheries-united-states
43. Bigelow K, Musyl MK, Poisson F, Kleiber P. Pelagic longline gear depth and shoaling. Fish Res. 2006; 77(2):173–83. https://doi.org/10.1016/j.fishres.2005.10.010
44. Boggs CH. Depth, capture time, and hooked longevity of longline-caught pelagic fish: timing bites of fish with chips. Fish Bull. 1992; 90(4):642–58. https://swfsc-publications.fisheries.noaa.gov/publications/CR/1992/9218.PDF
45. Howell EA, Hawn DR, Polovina JJ. Spatiotemporal variability in bigeye tuna (Thunnus obesus) dive behavior in the central North Pacific Ocean. Prog Oceanogr. 2010; 86(1–2):81–93. https://doi.org/10.1016/j.pocean.2010.04.013
46. Leung S, Thompson L, McPhaden MJ, Mislan KAS. ENSO drives near-surface oxygen and vertical habitat variability in the tropical Pacific. Environ Res Lett. 2019; 14(6):64020. http://dx.doi.org/10.1088/1748-9326/ab1c13
47. Zhou C, Wan R, Cao J, Xu L, Wang X, Zhu J. Spatial variability of bigeye tuna habitat in the Pacific Ocean: Hindcast from a refined ecological niche model. Fish Oceanogr. 2021; 30(1):23–37. https://doi.org/10.1111/fog.12500
48. Nicol S, Menkes C, Jurado-Molina J, Lehodey P, Usu T, Kumasi B, et al. Oceanographic characterisation of the Pacific Ocean and the potential impact of climate variability on tuna stocks and tuna fisheries. In: SPC Fisheries Newsletter. 2014. p. 37–48. http://www.spc.int/DigitalLibrary/Doc/FAME/InfoBull/FishNews/145/FishNews145_37_Nicol.pdf
49. Hampton J, Bigelow K, Labelle M. A summary of current information on the biology, fisheries and stock assessment of bigeye tuna (Thunnus obesus) in the Pacific Ocean, with recommendations for data requirement and future research. 1998. http://oceanfish.spc.int/en/publications/doc_download/540-1998-biology-fisheries-and-stock-assessment-of-bigeye-tuna-thunnus-obesus-in-the-pacific-ocean
50. Block BA, Keen JE, Castillo B, Dewar H, Freund E V., Marcinek DJ, et al. Environmental preferences of yellowfin tuna (Thunnus albacares) at the northern extent of its range. Mar Biol. 1997; 130(1):119–32. https://doi.org/10.1007/s002270050231
51. Holland KN, Kleiber P, Kajiura SM. Different residence times of yellowfin tuna, Thunnus albacares, and bigeye tuna, T. obesus, found in mixed aggregations over a seamount. Fish Bull. 1999; 97(2):392–5. https://spo.nmfs.noaa.gov/sites/default/files/17hollan.pdf

52. Lam CH, Tam C, Kobayashi DR, Lutcavage ME. Complex dispersal of adult yellowfin tuna from the main Hawaiian islands. Front Mar Sci. 2020; 7(138):1–13. https://doi.org/10.3389/fmars.2020.00138

53. Schaefer KM, Fuller DW, Block BA. Vertical movements and habitat utilization of skipjack (Katsuwonus pelamis), yellowfin (Thunnus albacares), and bigeye (Thunnus obesus) tunas in the equatorial eastern Pacific Ocean, ascertained through archival tag data. In: Nielsen JL, Arrizabalaga H, Fragoso N, Hobday A, Lutcavage M, Sibert J, editors. Tagging and Tracking of Marine Animals with Electronic Devices. New York: Springer; 2009. p. 121–44. https://doi.org/10.1007/978-1-4020-9640-2

54. Williams AJ, Allain V, Nicol SJ, Evans KJ, Hoyle SD, Dupoux C, et al. Vertical behavior and diet of albacore tuna (Thunnus alalunga) vary with latitude in the South Pacific Ocean. Deep Res Part II Top Stud Oceanogr. 2015; 113:154–69. https://doi.org/10.1016/j.dsr2.2014.03.010

55. Deary AL, Moret-Ferguson S, Engels M, Zettler E, Jaroslow G, Sancho G. Influence of central Pacific oceanographic conditions on the potential vertical habitat of four tropical tuna species. Pacific Sci. 2015; 69(4):461–75. https://doi.org/10.2984/69.4.3

56. Mugo R, Saitoh SI, Nihira A, Kuroyama T. Habitat characteristics of skipjack tuna (Katsuwonus pelamis) in the western North Pacific: a remote sensing perspective. Fish Oceanogr. 2010; 19(5):382–96. https://doi.org/10.1111/j.1365-2419.2010.00552.x

57. Picaut J, Ioualalen M, Delcroix T, Masia F, Murtugudde R, Vialard J. The oceanic zone of convergence on the eastern edge of the Pacific warm pool: A synthesis of results and implications for El Niño-Southern Oscillation and biogeochemical phenomena. J Geophys Res Ocean. 2001; 106(C2):2363–86. https://doi.org/10.1029/2000jc900141

58. PIFSC Fisheries Monitoring and Analysis Program. Hawaii longline logbook from 1991–2020. National Marine Fisheries Service, Pacific Islands Fish Sci Cent. 2021. https://inport.nmfs.noaa.gov/inport/2721

59. Hijmans RJ, Karney C, Williams E, Vennes C. geosphere: Spherical Trigonometry. 2017.

60. R Core Team. R: a language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computer; 2019. https://www.r-project.org

61. NOAA Coral Reef Watch. NOAA coral reef watch sea surface temperature CoralTemp v3.1 Monthly data for North Pacific Ocean, Jan. 1, 1991–Dec. 31, 2020. Silver Spring, Maryland, USA: NOAA Coral Reef Watch. 2021. https://oceanwatch.pifsc.noaa.gov/erddap/griddap/CRW_sst_v3_1_monthly.html

62. Woodworth-Jefcoats PA, Wren JLK. Toward an environmental predictor of tuna recruitment. Fish Oceanogr. 2020; 29(5):436–41. https://doi.org/10.1111/fog.12487

63. Porreca Z. Assessing ocean temperature's role in fishery production: A static model of western and central Pacific tuna fisheries. J Bioeconomics. 2021; 23(2). https://doi.org/10.1007/s10818-021-09311-1

64. Zeileis A, Hothorn T. Diagnostic checking in regression relationships. R News. 2002; 2(3):7–10.

65. Xu H, Minte-vera CV, Maunder M, Aires-da-Silva A. Status of bigeye tuna in the eastern Pacific Ocean in 2017 and outlook for the future. In: 9th meeting of the scientific advisory committee, Inter-American Tropical Tuna Commission: 14–18 May 2018. La Jolla, California, USA; 2018. p. 1–12. https://www.iattc.org/getattachment/5c789eea-0e49-4b2b-a1d5-61dd280139f2/SAC-09-05-EN_Bigeye-tuna-assessment-for-2017.pdf

66. Bell JD, Allain V, Gupta AS, Johnson JE, Hampton J, Hobday AJ, et al. Chapter 14: Climate change impacts, vulnerabilities and adaptations: western and central Pacific Ocean marine fisheries. In: Impacts of climate change on fisheries and aquaculture: synthesis of current knowledge, adaptation and mitigation options. Rome: FAO; 2018. http://www.fao.org/3/I9705EN/i9705en.pdf

67. Timmermann A, Oberhuber J, Bacher A, Esch M, Latif M, Roeckner E. Increased El Niño frequency in a climate model forced by future greenhouse warming. Lett to Nat. 1999; 398:694–7. https://doi.org/10.1038/19505

68. Cai W, Santoso A, Collins M, Dewitte B, Karamperidou C, Kug J-S, et al. Changing El Niño–Southern Oscillation in a warming climate. Nat Rev Earth Environ. 2021; 2(9):628–44. http://dx.doi.org/10.1038/s43017-021-00199-z

69. Chan HL, Pan M. Fishing trip cost modeling using generalized linear model and machine learning methods–A case study with longline fisheries in the Pacific and an application in Regulatory Impact Analysis. PLOS One. 2021; 16(9). https://doi.org/10.1371/journal.pone.0257027 PMID: 34492086

70. Geslani C, Loke M, Takenaka B, Leung P. Hawaii's seafood consumption and its supply sources. Honolulu: University of Hawaii Joint Research Institute for Marine and Atmospheric Research, SOEST 12–01, JIMAR Contribution 12–379; 2012. 1–26 p. http://www.soest.hawaii.edu/pfrp/soest_jimar_rpts/leung_etal_hi_seafood_consumption.pdf

71. Wang B, Luo X, Yang YM, Sun W, Cane MA, Cai W, et al. Historical change of El Niño properties sheds light on future changes of extreme El Niño. Proc Natl Acad Sci U S A. 2019; 116(45):22512–7. https://doi.org/10.1073/pnas.1911130116