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Article

Incorporating Sea Surface Temperature into Bioeconomic Fishery Models: An Examination of Western and Central Pacific Tuna Fisheries

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Abstract: Ocean temperatures are increasing. Little work has been done to examine the effects that these changes will have on fishery production. The study at hand seeks to incorporate the influence of climate change into established bioeconomic fishery models. Stock biomass is approximated to be a function of sea surface temperature. Following a feasible generalized least squares regression using data from the Western and Central Pacific, the interaction between fishery effort and temperature is found to be statistically significant. From this model, various functional forms relating effort, catch, and temperature are specified. In particular, a function that returns an effort requirement given a target catch level and temperature forecast is generated.The importance of these tools for fishery management is explored through application to Western and Central Pacific tuna fisheries. Recommendations for extensions into future research are made and the foundation for a model of efficient effort allocation across time and the entirety of a management area, given changing temperatures, is specified.

Keywords: fishery; bioeconomic; sustainability; tuna; management

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1. Introduction

It is beyond doubt that ocean temperatures are rising globally. The past thirty years have seen mean January temperatures across the Pacific rise more than five percent[1]. These temperature increases cause dramatic habitat changes and will likely affect the biological processes and ecology of marine species. While there has already been a wealth of literature produced that examines the changes to abundance and distribution of various marine species, examinations of the interplay between these ecological changes and fishery processes and outcomes have only recently begun to receive their due attention.

Bioeconomic modeling methods are an ideal tool for this sort of analysis. The basis of the bioeconomic fishery model originated in the work of Schaefer (1954, 1957). Schaefer's model looked at fishery catch as a function of the interplay between effort, a species' growth rate, and that species' environment's natural carrying capacity (Schaefer, 1954). This model was notably expanded upon by Lynn et al. (1981). In this paper the model was expanded to include the influence of an environmental factor on a particular fishery. In this case, the impact of the mangrove area on a Florida crab fishery was examined. This model is notable in that the actual functional relationship between stock biomass and the environmental variable (mangrove area) was not known. Rather, Lynn et al. posited several potential functional forms, based on certain hypothesized marginal properties, and then utilized the form which validated these assumptions and best fit their data. Other notable bioeconomic models that seek to incorporate environmental influences include Barbier & Strand (1998) and Ellis & Fisher (1986). For a survey of various bioeconomic fishery models which incorporate environmental variables see Knowler (2002) and Foley et al. (2012).

There has been significantly less work done in incorporating temperature effects into fishery models. Bell (1972) provided one of the first examinations of its kind, in which he sought to model the relationship between lobster catch and sea surface temperature as a linear function. This work

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[1] Based on the years 1985-2015, data taken from:
NOAA, N. (2020, August 01). [NOAA Optimum Interpolation (OI) SST V2 (Top Dataset, noaa.oisst.v2, sst. mnmean), 1.0°, 1981-present]. Unpublished raw data.

provides the foundational basis for much of the research that has followed. Following in this vein are Sun et al. (2006), Garza-Gil et al. (2010), and Sanz et al. (2017); all studies in which the relationship between sea surface temperature and fishery catch were examined. However, none of these studies provide a replicable methodology that could be utilized for the purpose of the study at hand. Sun et al. (2006) did not seek to generate a general model relating temperature and catch, but rather sought to quantify the effect that the El Niño has on catch. Garza-Gil et al. (2010) focused their study on Sardines, which compared to various tuna species are not a highly migratory fish. As such, stock biomass data was readily available for their study. This allowed for the determination of a specific functional form relating temperature to the observed biomass. Sanz et al. (2017) examined a non-migratory species and utilized a general Cobb-Douglas production function, rather than the Schaefer (1954) model used in the study at hand.

Developing a generalized methodology for understanding the relationship between ocean temperature and fishery catch is crucial given the reliance on fisheries in much of the developing world. The focus of the study at hand is on the various tuna species fisheries of the Western Central Pacific. Tunas are extremely responsive to changes in temperature (Brill, 1994). He established that tunas regulate body temperature by swimming, and as such may be forced out of desirable habitat due to overheating (Brill, 1994, p. 205). As such, warming ocean temperatures put the future of locality specific tuna fisheries in jeopardy. Bell et al. (2013) elucidated the problem that this may pose for many of the small island developing states of the Pacific Ocean. These tuna fisheries provide a significant portion of government revenue and GDP to these small island states through domestic fleets, domestic tuna processing, and licensing fees to foreign fleets (Bell et al., 2013). Further, most inhabitants of these small island developing nations derive the majority of their dietary animal protein from fish (Bell et al., 2009). In fact, for one nation, the Solomon Islands, 92% of inhabitants' animal dietary protein is derived from fish (Bell et al., 2009, p. 66). Given the paramount role that tuna plays both in the scope of economic development and for food security in these small island states, and the manner in which tuna species are influenced by temperature changes in their environment, serious examination of the relationships between catch, effort, and temperature is warranted.

Lehodey et al. (2013) examined changes in spatial distribution of skipjack tuna catch in relation to oceanic temperature changes. However, their work did not seek to model the relation between catch and sea surface temperature, but rather to model spatial distribution changes. Monllor-Hurtado et al. (2017) modeled changes in tuna catch as a function of temperature and a latitude time interaction. Their model did not account for the impact of effort on catch or for the interplay between effort and temperature. They did, however, hypothesize that effort trends were related to catch trends as a result of fishery strategies changing with changes in stock abundance. Notably, Mediodia et al. (2020) recently released findings from a current working paper in which results obtained and methodology utilized in examining the relationship between sea surface temperature and tuna catch were similar to those of the paper at hand. Testing several functional relationships, a quadratic model was ultimately decided upon and utilized to quantify the effect of temperature on tuna, catch (Mediodia et al., 2020, p. 10). However, while their methodology and results are similar, the model in which those authors utilized was not derived directly from the established Schaefer (1954) model, as extended via the Lynn et al. (1981) model. As such, the model derived and expanded upon in the remainder of this paper differs in functional form and in the interpretation of its parameters.

The study at hand examines the relationship between catch, effort, and temperature for the tuna species of the Western Central Pacific. This is accomplished through the vehicle of a bioeconomic model, consistent with the theoretical foundations of Schaefer (1954, 1957). The incorporation of Sea Surface Temperature into this model allows for an adaptable form that is readily able to be utilized in the study of the fisheries of other migratory species. From this model optimal temperature and effort functions are derived. Statistical software packages were utilized to generate parameter values, which in turn were input into the optimal temperature and effort functions to provide optimal values for the fishery under examination. These optimal values are used to identify where overfishing is occurring, relative to temperature levels, and where decreases in catch-per-unit-effort can be expected based on temperature trends and predictions.

2. Theory and Model

The Shaefer (1954) model forms the basis for much of the work that has been done on bioeconomic fishery modeling. His model take the form of:

$$C_t = kB_tE_t - \frac{k^2}{r}B_tE_t^2 \quad (1)$$

Where:

C_t is the catch in period t,
k is a catchability coefficient,
B_t is the maximum potential biomass of the stock in period t,
E_t is the fishery effort in period t,
r is the stock's natural growth rate,

This model is often modified to include a lagged dependent variable, catch, term. This is because stock adjustment may not be instantaneous. This model takes the form:

$$C_t = kB_tE_t - \frac{k^2}{r}B_tE_t^2 + \lambda C_{t-1} \quad (2)$$

Lynn et al. (1981) expanded upon this model with their inclusion of the influence of an environmental variable upon maximum potential stock biomass. Based upon hypothesized marginal properties of the functional form of the relation between this environmental variable and maximum potential biomass, they utilized the following functional form:

$$B_t = m(lnM_{t-1}) \quad (3)$$

Where:

M_{t-1} is marshland acreage in the previous period

Incorporating (3) into (2) provided:

$$C_t = \beta_0 + \beta_1(lnM_{t-1})(E) - \beta_2(lnM_{t-1})(E^2) + \beta_3(C_{t-1}) + \varepsilon_t \quad (4)$$

Where:

β_0 is an intercept term,
β_1 is km,
β_2 is $m(\frac{k^2}{r})$,
β_3 is λ,
ε_t is an error term

For the study at hand, the relationship between maximum potential stock biomass and sea surface temperature, $B_t = f(temperature)$, was hypothesized to have the following marginal properties:

$\frac{\delta biomass}{\delta temperatur} > 0$ for $temperature < t^*$,
$\frac{\delta biomass}{\delta temperature} < 0$ for $temperature > t^*$,
and $\frac{\delta^2 biomass}{\delta temperature^2} < 0$

t^* is some optimum temperature level

The functional form for the maximum potential biomass and temperature relationship was posited to be[2]:

$$f(temperature) = B_t = -\alpha_1(t_t)^2 + \alpha_2(t_t) + \alpha_3 \quad (5)$$

Inputting (5) into (2) yields the following:

$$C_{tj} = \beta_0 + \beta_a(e_{tj})(-\alpha_1 t_{tj}^2 + \alpha_2 t_{tj} + \alpha_3) - \beta_b(e_{tj})^2(-\alpha_1 t_{tj}^2 + \alpha_2 t_{tj} + \alpha_3) + \beta_c C_{(t-1)j} + \varepsilon_t \quad (6)$$

Where:

β_0 is an intercept term,
β_a is catchability coefficient k,
β_b is $(\frac{k}{r}^2)$,
β_c is λ,
ε_t is an error term,
j indicates the particular geographic position of the observation

Multiplying this out provides:

$$C_{tj} = \beta_0 - \beta_a\alpha_1(e_{tj})(t_{tj}^2) + \beta_a\alpha_2(e_{tj})(t_{tj}) + \beta_a(e_{tj})(\alpha_3) + \beta_b\alpha_1(e_{tj})^2(t_{tj}^2) - \beta_b\alpha_2(e_{tj})^2(t_{tj}) - \beta_b(e_{tj})^2(\alpha_3) + \beta_c C_{(t-1)j} + \varepsilon_t \quad (7)$$

This can be simplified to[3]:

$$C_{tj} = \beta_0 - \beta_1(e_{tj})(t_{tj}^2) + \beta_2(e_{tj})(t_{tj}) + \beta_3(e_{tj}) + \beta_4(e_{tj})^2(t_{tj}^2) - \beta_5(e_{tj})^2(t_{tj}) - \beta_6(e_{tj})^2 + \beta_7 C_{(t-1)j} + \varepsilon \quad (8)$$

Where:

$$\beta_a\alpha_1 = \beta_1$$
$$\beta_a\alpha_2 = \beta_2$$
$$\beta_a\alpha_3 = \beta_3$$
$$\beta_b\alpha_1 = \beta_4$$
$$\beta_b\alpha_2 = \beta_5$$
$$\beta_b\alpha_3 = \beta_6$$
$$\beta_c = \beta_7$$

In theory both temperature and effort can vary without bounds[4]. As such, the optimum combination of effort and temperature can be easily determined. First obtained is the catch maximizing optimal effort level for any given temperature. This conditional effort function is:

$$E(\underline{t}_{tj}) = \frac{\beta_1(t_{tj})^2 - \beta_2(t_{tj}) - \beta_3}{2\beta_4(t_{tj})^2 - 2\beta_5(t_{tj}) - 2\beta_6} \quad (9)$$

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[2] This model and other functional forms were tested using catch per unit effort as a proxy for biomass. The model utilized was best able to explain variation in CPUE.

[3] It bears stating that the model will be input into statistical software with positive signs on all coefficients. As such, when interpreting regression results the signs of several of the coefficient values will need to be inverted.

[4] Ocean temperatures are of course actually limited by the freezing point of the ocean and by its boiling point. However, for the purposes of this study these improbable extremes can be neglected.

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The optimal effort level and temperature combination obtained is:

$$E^{*} = \frac{\beta_1-\beta_2{}^2-\beta_3}{2(\beta_4-\beta_5{}^2-\beta_6)} \text{ and } t^{*} = \frac{\beta_2+\beta_5}{2(\beta_1+\beta_4)} \quad (10) \text{ and } (11)$$

The marginal rate of technical substitution of effort for temperature can be found easily enough:

$$MRTS_{e\,for\,t} = -\left(\frac{\delta C_{tj}}{\delta t_{tj}}\right)/\left(\frac{\delta C_{tj}}{\delta e_{tj}}\right) \quad (12)$$

$$MRTS_{e\,for\,t} = \frac{2\beta_1(e_{tj}\cdot t_{tj})-\beta_2 e_{tj}-2\beta_4(e_{tj})^2(t_{tj})+\beta_5(e_{tj})^2}{-\beta_1(t_{tj})^2+\beta_2 t_{tj}+\beta_3+2\beta_4(e_{tj})(t_{tj})^2-2\beta_5(e_{tj})(t_{tj})-2\beta_6(e_{tj})} \quad (13)$$

The necessary algebra is a bit more complicated in determining the functional form conditional effort function if both temperature and catch level are held constant. Some manipulation, and the quadratic formula yield:

$$E(\underline{C}_{tj},\underline{t}_{tj}) = \frac{(-\beta_1 t_{tj}^2+\beta_2 t_{tj}+\beta_3)-\sqrt{(-\beta_1 t_{tj}^2+\beta_2 t_{tj}+\beta_3)^2-4(\beta_4 t_{tj}^2-\beta_5 t_{tj}-\beta_6)(\beta_7 C_{(t-1)(j)}+\beta_0-C_{tj})}}{2(\beta_4 t_{tj}^2-\beta_5 t_{tj}-\beta_6)} \quad (14)$$

Since ocean temperature levels are beyond the control of fishery managers, the conditional effort functions will be the primary vehicles utilized to evaluate the sustainability of the tuna fisheries of the Western Central Pacific, and to make recommendations as to what changes should be made to best protect these fisheries in the face of rising ocean temperatures.

3. Data

Data utilized came from a variety of sources. Catch data was taken from the Western & Central Pacific Fisheries Commission's (WCPFC) "Public Domain Aggregate Catch/Effort" dataset. This data was provided in a monthly time series of 5° by 5° gridded coordinate squares. Longline effort was used in this study's analysis due to the random sampling effect inherent in longline fishing methods. There is little targeting of effort beyond selection of a generalized geographic area in which to set the longline, which can be in excess of 20 miles in length[5]. The variety and abundance of species that are caught on the longline, in effect, will represent a more or less randomly generated sample of the area's biodiversity.

Temperature data was drawn from the NOAA Optimum Interpolation (OI) SST V2 dataset. This dataset was provided in a monthly time series of 1° by 1° gridded coordinate squares, with sea surface temperatures provided in monthly mean °C. Since both types of data were provided in different coordinate systems, to coordinate this SST data with the catch and effort data the 1° by 1° gridded coordinate square corresponding to the bottom left corner of each 5° by 5° square was used as representative of the entire 5° by 5° square.

The timespan represented by the data ranged from January 1985 to December 2018. Data was given in a monthly format. Due to the large size of the dataset, any observation (coordinate square in a particular month) which lacked any fishing effort was dropped from the dataset. This is

[5] Source: NOAA fisheries

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logically consistent, as an observation absent any effort is unable to provide information on fishery trends relevant to the study at hand. After dropping these observations 408 unique time periods remained represented, along with 321 unique coordinate squares. Further observations were dropped by the statistical software while computing regression estimates, due to incomplete observational data.

Three unique species of tuna were examined separately: yellowfin, albacore, and big eye. It bears stating that effort is not species specific. The same unit of effort is capable of catching any of these tuna species, or any number of other marine species, with likelihoods varying solely based on distribution and stock abundance. Also as a caveat to the data, the minimum effort level reported was 100,000 hooks in a coordinate square in a particular month. Small scale fishing effort was not recorded or not not reported by WCPFC. However, the average longline has some 3,000 hooks[6]. As such, the minimum level of effort recorded is sufficient to capture the bulk of commercial fishing activity in each roughly 87,000 square mile 5° by 5° coordinate square.

Table of variables				
Effort	Provided in 100's of hooks, converted to number of hooks			
		mean= 541477.2		st dev. = 666728.3
			min=100000	max=46455380
Yellowfin Catch	Provided in metric tonnes, converted to kg			
		mean=57098.52		st dev.= 94043.9
			min=0	max=1279519
Albacore Catch	Provided in metric tonnes, converted to kg			
		mean=47936.72		st dev.=107302.6
			min=0	max=2641909
Bigeye Catch	Provided in metric tonnes, converted to kg			
		mean= 49775.5		st dev.=75800.9
			min=0	max=1609489
Sea Surface Temperature	Provided in degrees celsius			
		mean=26.41		st dev.=3.866
			min=7.7	max=30.97
Latitude	min=-50	max=40		
Longitude	min=105	max=225		
n= 47,292				

Table 1. Table of variables and summary statistics

[6] Source: FAO fisheries

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Mean Species Catch Per Unit Effort by Latitude			
Plus or minus degrees	Yellowfin	Albacore	Bigeye
0	0.177	0.003	0.165
5	0.153	0.007	0.162
10	0.137	0.039	0.158
15	0.108	0.153	0.066
20	0.066	0.176	0.038
25	0.054	0.167	0.041
30	0.040	0.206	0.066
35	0.034	0.174	0.073
40	0.029	0.207	0.022

Table 2. Mean catch per unit effort by species and latitudinal distance from equator

4. Empirical Methodology and Results

The model derived in equation (8) was fit to the data at hand using a feasible generalized least squares (FGLS) panel data method. The FGLS method was selected due to the number of time periods being examined exceeding the number of coordinate squares examined. Each gridded coordinate square was taken as a separate panel with every month representing a separate time interval. Tests were conducted for autocorrelation and for heteroskedasticity. Wooldridge tests for autocorrelation in panel data were conducted for the specified model for each species. The models were each tested with and without the presence of the lagged dependent variable. The Wooldridge test takes there being autocorrelation as the null hypothesis. Its test statistic follows an F distribution. This null hypothesis was rejected in each case and autocorrelation was found to be present in each model.

To proceed in testing for heteroskedasticity, FGLS models were specified with homoskedastic and with heteroskedastic panel variance. The two models were then compared with a likelihood ratio test. This test's statistic follows a chi-squared distribution. The test takes homoskedasticity as the null hypothesis. The test for the model for each species failed to reject the null hypothesis. The results of these specification tests are summarized in table 3.

Het test	Liklihood Ratio Test Between Model correcting for Heteroskedasticty and and model without		
	Yellowfin	Albacore	Bigeye
Chi Square	-11185.79	-113407.56	-25543.1
Heteroskedasticty?	No	No	No

Autocorrelation Test	Wooldridge Test for Autocorrelation in Panel Data, without lagged term		
	Yellowfin	Albacore	Bigeye
F statistic	161.094	203.442	92.84
Autocorrelation?	Yes	Yes	Yes

Autocorrelation Test	Wooldridge Test for Autocorrelation in Panel Data, withlagged term		
	Yellowfin	Albacore	Bigeye
F statistic	389.824	225.252	384.211
Autocorrelation?	Yes	Yes	Yes

Table 3. Autocorrelation and heteroskedasticity testing results

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Due to missing observations the data could not be tested with typical unit root tests. Instead, by regressing the model's two stochastic elements, effort and temperature, against their own lag, a unit root test was able to be approximated. The coefficient generated was then tested against a null hypothesis of unit equality. The same process was repeated for the various species' catch observations on their respective lags. In all cases, this null hypothesis was rejected and the possibility of a unit root was ruled out. This indicates stationarity in the time trends that can be addressed adequately by the one period autoregressive means employed. These test statistics are reported in table 4.

	Temperature	Effort	Yellowfin	Albacore	Bigeye
Chi Squared	2761.78	5842.34	4511.23	6419.48	7918.41

Table 4. Unit root test results

Following the results of these tests, the models were fit with specifications for homoskedastic variance and the presence of autocorrelation within panels. These regression results are summarized in table 5.

Models fit with feasible generalized least square method, with correction for autocorrelation

	Yellowfin	Abacore	Bigeye
Temperature Squared times Effort	0.000331***	-0.00119***	-0.000632***
	(10.89)	(-27.15)	(-18.92)
Temperature times Effort	-0.00997***	0.0418***	0.0317***
	(-6.56)	(19.15)	(18.99)
Effort	0.0958***	-0.182***	-0.332***
	(5.06)	(-6.67)	(-15.93)
Temperature Squared times Effort Squared	-2.79e-11***	1.07e-10***	6.82e-11***
	(-2.93)	(8.14)	(6.77)
Temperature times Effort Squared	1.50e-09***	-4.77e-09***	-3.27e-09***
	(2.92)	(-6.71)	(-6.02)
Effort Squared	-2.20e-08***	4.71e-08***	3.59e-08***
	(-3.15)	(4.86)	(4.85)
Lag of Yellowfin Catch	0.429***		
	(117.08)		
Lag of Albacore Catch		0.382***	
		(93.79)	
Lag of Bigeye Catch			0.378***
			(89.95)
Constant	-5431.1***	-7826.6***	1481.7***
	(-11.10)	(-10.89)	(2.59)
Observations	36506	36506	36506
Panels	297	297	297
Chi-Squared	64474.8	23698.5	20548.1
Chi-Squared Type	Wald	Wald	Wald
Rho	.1829986621591862	.2556269970113945	.2534115351404863
Rho Type	regress	regress	regress

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Regression output results

It bears noting that FLGS methodologies do not produce a standard R^2 goodness of fit measure for the model. As such, the correlation coefficient between the model's fitted and observed values is used instead to assess model fit. These values are reported below.

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Correlation between observed and fitted values			
	Yellowfin	Albacore	Bigeye
Correlation	0.8479	0.7495	0.689

Table 6. Correlation coefficients between fitted and observed values

The parameter values derived from these estimates can be input into equations (9) through (14) to generate useful predictions regarding the management of the region's fisheries. Equation's (10) and (11) will provide the optimum effort and temperature combinations for each species. These combinations are a useful benchmark against which to measure a fishery's current state. These results are reported in table 7. It is of note that Yellowfin catch is maximized at such low temperature levels, near the minimum point at which catch is observed. This is more a factor of the mathematics of the model, in which the extremely high level of effort plays a larger part. This illustrates that these hypothetical optimum effort and temperature combinations are not an ideal standard for fishery management.

	Yellowfin	Albacore	Bigeye
Temp	15.10	17.60	25.10
Effort	2180000.00	1463854.77	3630357.19

Table 7. Optimum effort and temperature and effort combinations

Equation (9) provides a much more useful measure for setting fishery goals with the objective of maximizing catch. Approximating necessary effort levels to maximize fishery yields in the face of changing ocean temperatures allows for fishery managers to plan accordingly against the forecasts of oceanographers and climate scientists. The results, reported below, show that the optimal effort level respective to temperature for each species is unique. Catch of Bigeye at low temperatures was nearly negligible in the data, as was the catch of Albacore at high temperatures. Optimal effort levels trend differently for each species group. Maximizing Albacore catch would require higher effort levels at lower temperatures, while both Bigeye and Yellowfin catch are maximized with higher effort levels at higher temperatures. These effort levels are observably quite high, due to their representing the highest level of extraction possible without consideration for the long term economic or biological sustainability of the yield. As such, they solely represent catch maximizing effort levels at various temperatures in an open access environment. The primary value of these estimates is in illustrating the optimal trends in effort respective of temperature; that each species of tuna responds differently to different temperature levels.

Optimal Effort Level Given Temperature for Catch Maximization			
	Yellowfin	Albacore	Bigeye
15°	1.80E+06	2.36E+08	-
20°	4.56E+06	1.62E+07	1.11E+07
25°	1.38E+07	1.13E+07	1.02E+07
30°	2.24E+07	-	3.06E+07

Table 8. Optimal effort levels at varying temperatures

Equation (13) is interesting in that it is able to provide us with tradeoffs inherent in maintaining a consistent level of catch as temperatures change. It is apparent from the equation that

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its resulting value will change as the values of effort and temperature themselves change. Despite this, it can still be a useful measure for assessing what changes would be necessary to maintain a given level of input. For example, in an arbitrary recently observed period, January 2018, the fishery located out of Honolulu, Hawaii (found in the 20°N by 155° W coordinate square) observed a catch of roughly 18,000 kg of Yellowfin tuna with roughly 180,000 longline hooks set and a mean sea surface temperature of 27.1°C. If this location's fishery managers were to desire to maintain this level of catch in the face of an expected 1° rise in ocean temperatures, they would need some 21,000 more hooks to be set. This result demonstrates a decreasing catch per unit effort, and implies a declining stock biomass as temperatures increase. The value of this sort of tool for managing and assessing fishery goals is apparent.

Perhaps most useful of the tools derived is equation (14) which allows fishery managers to determine requisite effort levels based upon catch targets and temperature forecasts. Catch targets can be set with aims based in maximum economic yield fishery management (MEY) or maximum sustainable yield fishery management strategies (MSY). Whatever target levels are set, this equation will allow fishery managers to determine the requisite effort level needed to meet that target in the face of climate predictions. Those seeking to minimize total effort while reaching a particular fishery goal for the entirety of an exclusive economic zone (EEZ) can set up a simple optimization problem to solve for the most efficient allocation of effort across their EEZ, using the form:

$$min\, TE_t = \sum_{j=1}^{n} E_{tj}(C_{tj}, \underline{t}_{tj}) \text{subject to } \sum_{j=1}^{n} C_{tj} = \underline{TC_t} \tag{15}$$

Where:

TE= total effort, the summation of effort in each coordinate square of the EEZ

TC= a preset desired total catch target level across the EEZ

C_{tj}= the catch in each coordinate square

j=an individual coordinate square in the EEZ

n= the total number of coordinate squares in the EEZ

While the math for deriving this solution will undoubtedly grow quite complex, the relatively simple set up provides a useful framework for managing fisheries in the face of increasing ocean temperatures. This model can be readily adapted for the allocation of effort across time with little modification:

$$min\, TE = \sum_{t=0}^{n} \sum_{j=0}^{n} E_{tj}(C_{tj}, \underline{t}_{tj}) \text{subject to } \sum_{j=1}^{n} C_{tj} = \underline{TC_t} \tag{16}$$

Returning to the simple case of equation (14), where we are simply looking at the necessary effort for a single coordinate square, an example will help elucidate the usefulness. Suppose those who manage the fishery immediately surrounding Fiji's capital Suva (found in the 15°S by 175° E coordinate square) desire to increase their monthly Yellowfin catch from 28,000 to 30,000 kg in the face of an expected quarter degree rise in ocean temperatures, to 29.6°.In this situation, the fishery should seek to deploy around 260,000 hooks to reach this goal. It also bears stating that this model can readily be adapted for management in the multi-species fishery case. To reach a particular target level for all species, all that needs to be done is to calculate the effort required for each species in the same time period and coordinate square. The maximum of these values will be the best estimate for the effort needed to reach all of the species target goals, as longline effort is largely indiscriminate.Such a strategy will likely result in excess catches of the lesser required effort

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species. As such, conservation minded fishery managers would do well to employ the opposite strategy, utilizing the minimum effort value obtained and keeping all catch levels below targets.

5. Discussion

The above section has visited the applied value of the equations derived in the model specification and theory section of this paper. Ocean temperature is shown to have a significant effect on fishery yield, at least in the specific context examined: tuna fisheries of the Western and Central Pacific Ocean. The equations derived in this paper are of clear value to fishery managers, and point to the role that consideration of temperature must play in fishery management moving forward as the planet is faced with rising ocean temperatures.

All of the applications above have been focused towards the future, centered on the value that these tools have in planning for future fishery yield. However, they also have a diagnostic value in identifying strategies that are not best suited for our era of climate change. As with the derived models' value in planning for the future, much of the diagnostic value could be improved upon with the logical progression of the models beyond the scope of this paper, stemming from the point of equations (15) and (16). These models provide a basis for evaluating past allocative efficiency of effort resources and for identification of EEZs in which resources could have been better utilized to achieve the same or better results. While this avenue of discussion is beyond the scope of the study at hand, and perhaps provides a good starting point for future research, it is evident, at least logically, that the models herein described have the potential to improve upon the capabilities of current fishery management methodologies. The addition of sea surface temperature into existing bioeconomic modeling methodologies is essential to better mirror the realities of the marine ecosystem.

Equation (13), which allows us to examine necessary changes in effort level to maintain a constant catch level as temperature changes, demonstrates the direction in which stock biomass is trending with temperature change. It is able to demonstrate the simple fact that in many locales increasing temperatures are resulting in decreasing catch per unit effort.

With the model as derived and limited herein we are able to identify locales that are being less than efficient in their deployment of fishery effort, relative to their sea surface temperature. However, all of these equations for deriving particular optimal effort levels given temperature solely provide for immediate term catch maximizing levels of effort. This, for obvious reasons, is not the best tool for sustainable fishery management. In order to sustainably manage these fisheries in the face of climate change, target catch levels need to be set that are aimed at maintaining long term stock viability in a dynamic environment. Only with these targets appropriately and accurately set, are the tools derived in equations (14), (15), and (16) able to contribute to fishery sustainability.

Setting appropriate target catch levels that take into consideration stock viability, climate change, and shifting demand due to changing human population dynamics will allow the models developed herein to be their most useful. Climate change must factor into both ends of the equation, temperature needs to be considered both in determining the ideal supply and in determining how best to achieve that supply level. The models derived have demonstrated, for all three tuna species examined, a high level of statistical significance for the interaction between temperature and fishery effort. It seems intuitive that the environment affects the production function of this natural resource. However, quantification of this relationship is necessary to effectively address the problems that climate change is causing for stock depletion, food security, and small island developing state economic viability.

6. Conclusion

This study has established the significant relationship that ocean temperatures play in the production function for three subspecies of highly migratory pelagic fish. The models derived provide a theoretical framework for extending the analysis to a broader range of species. From this model, various equations have been derived that are able to provide fishery managers with useful metrics and tools for planning and evaluation of fishery management strategies. It is crucial that as the effects of climate change become more pronounced fishery managers do not neglect the role that ocean temperatures play in the fishery production function.

The study at hand faced some data limitations, and would have benefited from higher resolution data. This would have allowed us to utilize smaller geographic coordinate squares and to more precisely estimate effects. Future study with higher resolution data would do well to also look at the spatial trends as well.

Several clear routes for future research have been made apparent by this study. Foremost, equations (15) and (16) have the potential to provide an extremely useful fishery management framework if properly explored. This is especially true if they are able to be paired with catch targets that accurately account for the changes to species' ecosystems and human population growth. Further, other environmental factors would do well to be incorporated into the general model of equation (5) and all of the other functions derived from it. Factors such as changing levels of ocean acidity, plankton distribution, and oceanic pollution would add immensely to the value of this model.

Despite the data limitations and the narrow scope of the model's derivations, it has contributed significantly in providing a base formula to aid fishery managers in determining what level of effort need be employed to reach management goals. Climate change is a factor that needs to be considered in all aspects of natural resource management for the sake of food security and economic development. This examination of the Western and Central Pacific's tuna fisheries has established the role that temperature plays in the marine resource production function.

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Appendix A

Using CPUE as a Proxy for Biomass, regressed against temperature

	Equation (5)
Temperature	0.0904^{***}
	(4.48)
Temperature Squared	-0.00155^{***}
	(-3.62)
Constant	-0.842^{***}
	(-3.63)
Observations	47292
R2	0.155
Chi-Squared	58.91
Chi-Squared Type	Wald

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. Results from testing equation (5)

References

1. (WCPFC), W. (2020, July 27). [Public Domain Aggregated Catch/Effort Data]. Unpublished raw data.
2. Barbier, E. B., & Strand, I. (1998). Valuing Mangrove-Fishery Linkages – A Case Study of Campeche, Mexico. *Environmental and Resource Economics, 12*(2), 151-166. doi:10.1023/a:1008248003520
3. Bell, F. W. (1972). Technological Externalities and Common-Property Resources: An Empirical Study of the U.S. Northern Lobster Fishery. *Journal of Political Economy, 80*(1), 148-158. doi:10.1086/259867
4. Bell, J. D., Allain, V., Gupta, A. S., Johnson, J. E., Hampton, J., Hobday, A. J., . . . Williams, P. (2018). Climate change impacts, vulnerabilities and adaptations: Western and Central Pacific Ocean marine fisheries (955699647 744431480 M. Barange, 955699648 744431480 T. Bahri, 955699649 744431480 M. C. Beveridge, 955699650 744431480 K. L. Cochrane, 955699651 744431480 S. Funge-Smith, & 955699652 744431480 F. Poulain, Eds.). In *Impacts of climate change on fisheries and aquaculture* (pp. 305-324). Rome, IT: Food and Agriculture Organization of the United Nations.
5. Bell, J. D., Kronen, M., Vunisea, A., Nash, W. J., Keeble, G., Demmke, A., . . . Andrefouet, S. (2009). Planning the use of fish for food security in the Pacific. *Marine Policy, 33*(1), 64-76. doi:https://doi.org/10.1016/j.marpol.2008.04.002
6. Bell, J. D., Reid, C., Batty, M. J., Lehodey, P., Rodwell, L., Hobday, A. J., . . . Demmke, A. (2012). Effects of climate change on oceanic fisheries in the tropical Pacific: Implications for economic development and food security. *Climatic Change, 119*(1), 199-212. doi:10.1007/s10584-012-0606-2
7. Brill, R. W. (1994). A review of temperature and oxygen tolerance studies of tunas pertinent to fisheries oceanography, movement models and stock assessments. *Fisheries Oceanography, 3*(3), 204-216. doi:10.1111/j.1365-2419.1994.tb00098.x
8. Charlton, K. E., Russell, J., Gorman, E., Hanich, Q., Delisle, A., Cambell, B., & Bell, J. (2016). Fish, food security and health in Pacific Island countries and territories: A systematic literature review. *BMC Public Health, 16*(285). doi:10.1186/s12889-016-2953-9
9. Ellis, G. M., & Fisher, A. C. (1986). Valuing the Environment as an Input. *CUDARE Working Papers, 198357*. doi:DOI: 10.22004/ag.econ.198357
10. FAO. (2020). Industrial Tuna Longlining. Retrieved October 21, 2020, from http://www.fao.org/fishery/fishtech/1010/en
11. Fisheries, N. (2019, May 09). Fishing Gear: Pelagic Longlines. Retrieved October 21, 2020, from https://www.fisheries.noaa.gov/national/bycatch/fishing-gear-pelagic-longlines
12. Foley, N. S., Armstrong, C. W., Kahui, V., Mikkelsen, E., & Reithe, S. (2012). A Review of Bioeconomic Modelling of Habitat-Fisheries Interactions. *International Journal of Ecology, 2012*, 1-11. doi:10.1155/2012/861635
13. Garza-Gil, M. D., Torralba-Cano, J., & Varela-Lafuente, M. M. (2010). Evaluating the economic effects of climate change on the European sardine fishery. *Regional Environmental Change, 11*(1), 87-95. doi:10.1007/s10113-010-0121-9
14. Gillett, R. (2009). *Fisheries in the Economies of the Pacific Island Countries and Territories*. Mandaluyong City, PH: Asian Development Bank.
15. Knowler, D. (2002). A Review of Selected Bioeconomic Models with Environmental Influences in Fisheries. *Journal of Bioeconomics, 4*(2), 163-181. doi:10.1023/a:1021151809501

16. Lehodey, P., Senina, I., Calmettes, B., Hampton, J., & Nicol, S. (2012). Modelling the impact of climate change on Pacific skipjack tuna population and fisheries. *Climatic Change, 119*(1), 95-109. doi:10.1007/s10584-012-0595-1
17. Lynne, G. D., Conroy, P., & Prochaska, F. J. (1981). Economic valuation of marsh areas for marine production processes. *Journal of Environmental Economics and Management*, *8*(2), 175-186. doi:10.1016/0095-0696(81)90006-1
18. Massey, D. M., Newbold, S. C., & Gentner, B. (2006). Valuing water quality changes using a bioeconomic model of a coastal recreational fishery. *Journal of Environmental Economics and Management*, *52*(1), 482-500. doi:10.1016/j.jeem.2006.02.001
19. Mediodia, H. J., Kahui, V., & Noy, I. (2020). Sea Surface Temperature and Tuna Catch in the Eastern Pacific Ocean Under Climate Change. *CESifo Working Paper,* (8533).
20. Monllor-Hurtado, A., Pennino, M. G., & Sanchez-Lizaso, J. L. (2017). Shift in tuna catches due to ocean warming. *PLoS ONE, 12*(6). doi:10.1371/journal.pone.0178196
21. NOAA, N. (2020, August 01). [NOAA Optimum Interpolation (OI) SST V2 (Top Dataset, noaa.oisst.v2, sst. mnmean), 1.0°, 1981-present]. Unpublished raw data.
22. Russo, T., Parisi, A., Garofalo, G., Gristina, M., Cataudella, S., & Fiorentino, F. (2014). SMART: A Spatially Explicit Bio-Economic Model for Assessing and Managing Demersal Fisheries, with an Application to Italian Trawlers in the Strait of Sicily. *PLoS ONE*, *9*(1). doi:10.1371/journal.pone.0086222
23. Sanz, N., Blanchard, F., & Lampert, L. (2017). On the influence of environmental factors on harvest: The French Guiana shrimp fishery paradox. *Environmental Economics and Policy Studies, 19*, 233-247. doi:https://doi.org/10.1007/s10018-016-0153-6
24. Schaefer, M. (1991). Some aspects of the dynamics of populations important to the management of the commercial marine fisheries. *Bulletin of Mathematical Biology*, *53*(1-2), 253-279. doi:10.1016/s0092-8240(05)80049-7
25. Schaefer, M. B. (1953). Some aspects of the dynamics of populations important to the management of the commercial marine fisheries. *Inter-American Tropical Tuna Commission Bulletin*, *1*(2), 23-56. doi:10.1007/bf02464432
26. Schaefer, M. B. (1957). A study of the dynamics of the fishery for yellowfin tuna in the Eastern Tropical Pacific Ocean. *Inter-American Tropical Tuna Commission Bulletin, 2*(6), 243-285. Retrieved September 30, 2020, from http://aquaticcommons.org/id/eprint/3531
27. StataCorp, LLC. (2019). Xtgls — Fit panel-data models by using GLS. In 1010016122 777650530 S. LLC (Ed.), *Stata Longitudinal-DataPanel-Data Reference Manual Release 16* (pp. 197-208). College Station, TX: Stata Press. Retrieved October 26, 2020, from :https://www.stata.com/manuals/xt.pdf
28. Sun, C., Chiang, F., Tsoa, E., & Chen, M. (2006). The effects of El Niño on the mackerel purse-seine fishery harvests in Taiwan: An analysis integrating the barometric readings and sea surface temperature. *Ecological Economics*, *56*(2), 268-279. doi:10.1016/j.ecolecon.2005.02.001
29. Wiggins, V., & Poi, B. (2020). How do I test for panel-level heteroskedasticity and autocorrelation? Retrieved October 26, 2020, from https://www.stata.com/support/faqs/statistics/panel-level-heteroskedasticity-and-autocorrelation/
30. Zivot, E. (2005, April 05). Unit Root Tests. Retrieved October 26, 2020, from https://faculty.washington.edu/ezivot/econ584/notes/unitroot.pdf

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