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# Toward an environmental predictor of tuna recruitment

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## Abstract

Bigeye tuna are of global economic importance and are the primary target species of Hawaii's most valuable commercial fishery. Due to their high commercial value, bigeye tuna are relatively well studied and routinely assessed. Larval and adult bigeye surveys have been conducted for many years and are supported by ongoing research on their physiology and life history. Yet, modeling stock dynamics and estimating future catch rates remain challenging. Here, we show that an appropriately lagged measure of phytoplankton size is a robust predictor of catch rates in Hawaii's bigeye tuna fishery with a forecast window of four years. We present a fishery-independent tool with the potential to improve stock assessments, aid dynamic fisheries management, and allow Hawaii's commercial longline fishing industry to better plan for the future.

**KEYWORDS**

bigeye tuna, fisheries, larval survival, phytoplankton, recruitment, *Thunnus obesus*, tuna

## 1 | INTRODUCTION

Bigeye tuna (*Thunnus obesus*) are the primary target species of Hawaii's most valuable commercial fishery, a longline fishery with landings that are valued at over $100 million (NMFS, 2018b) and that account for nearly half the United States tuna landings (NMFS, 2018a, 2018b). A reliable predictor of targeted species catch rates could help the fishery time fishing activity and plan capital improvements. It could also potentially inform adaptive management and facilitate ecosystem-based fisheries management.

Due to their high commercial value, bigeye and other tunas are well studied. Surveys of larval (Nishikawa, Honma, Ueyanagi, & Kikiawa, 1985) and adult (Kume, 1969) bigeye tuna extend back over 50 years, and their life history, physiology, and habitat (e.g., Block & Stevens, 2001, and references therein; Lehodey et al., 2010 and references therein, Muhling et al., 2017 and references therein) are relatively well understood. Pacific bigeye tuna are also regularly assessed (most recently by Vincent, Pilling, & Hampton, 2018; Xu, Minte-Vera, Maaunder, & Aires-da-Silva, 2018).

Despite bigeye tuna being routinely studied, factors influencing their recruitment remain poorly understood (e.g., Abascal et al., 2018; Xu et al., 2018). ENSO cycles are thought to influence bigeye recruitment strength in the eastern Pacific Ocean, though the exact nature of this relationship is unclear (Xu et al., 2018). Although larval foraging success is an important component of recruitment (Llopiz & Hobday, 2015; Muhling et al., 2017), it is not currently possible to quantify the effects to a population level. Thus, environmental and ecosystem metrics for recruitment are not routinely incorporated into bigeye tuna stock assessments or management.

A recent study of interannual variability in the Hawaii longline fleet's catch determined that high catch rates of small (<15 kg) bigeye tuna precede peaks in overall catch rates by two years (Wren and Polovina, in review). This relationship is due to the age structure of the longline catch, which is dominated by 4- to 5-year-old fish. The smaller size class coincides with fish that are two years old, hence the two-year time lag between catch rates of small bigeye and overall catch.

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The recruitment indicator developed by Wren and Polovina (in review) raises two important points: one, there is coherent age structure across the bigeye tuna population targeted by Hawaii's longline fleet; and two, it is possible to identify the timing of recruitment of distinct cohorts to the fishery. The presence of larval bigeye tuna across much of the fishery's footprint further supports these points (Nishikawa et al., 1985; Reglero, Tittensor, Álvarez-Berastegui, Aparicio-González, & Worm, 2014). Here, we build on these results and propose using an environmental driver of bigeye tuna recruitment as a forecasting tool. We hypothesize that median phytoplankton size, $M_{D50}$, can be used to forecast bigeye tuna catch rates four years in advance. We take $M_{D50}$ to be a proxy for the quality of food available to larval and juvenile bigeye tuna, with greater $M_{D50}$ values indicative of higher food quality. Greater $M_{D50}$ values would indicate that there are more large phytoplankton and in turn more prey available for the zooplankton upon which larval bigeye tuna feed. Increased prey availability would then lead to more bigeye tuna surviving to reach adulthood (Hjort, 1914). The 4-year forecast window is based on the age structure of the catch, as described above. $M_{D50}$ can be derived from publicly available satellite remotely sensed data (Barnes, Irigoien, De Oliveira, Maxwell, & Jennings, 2011) and could possibly be used to improve stock assessments for bigeye tuna and other species.

Being able to anticipate fishery performance with some confidence could also help improve fishery management. Recent stock assessments have intermittently identified bigeye tuna as experiencing overfishing in the western and central Pacific (Abascal et al., 2018; Harley, Davies, Hampton, & McKechnie, 2014; McKechnie, Pilling, & Hampton, 2017) and eastern Pacific (Abascal et al., 2018; Aires-da-Silva & Maunder, 2015; Xu et al., 2018). Such determinations indicate a potential strain on the fishery's ecological sustainability. Knowing in advance which years may produce lower catch rates resulting from reduced abundance could enable fishery managers to take adaptive measures and avoid further stressing the population (Tommasi et al., 2017). Such an approach—using size structure at the base of the food web to inform estimates of top predator abundance—would be a step toward ecosystem-based fisheries management (EBFM; Pikitch et al., 2004), which has yet to be implemented in Hawaii's longline fishery.

## 2 | MATERIALS AND METHODS

### 2.1 | Environmental data

We estimated median phytoplankton cell mass in pg C ($M_{B50}$) following the methodology of Barnes et al. (2011) as shown in Equation 1:

$$\log_{10}\left(M_{B50}\right) = 0.929\left(\log_{10}\left(chl-a\right)\right) - 0.043\left(SST\right) + 1.340 \quad (1)$$

where chl-a is chlorophyll-a in mg/m³, and SST is sea surface temperature in °C. We then transformed cell mass to cell size in equivalent spherical diameter (ESD) in μm, hereafter $M_{D50}$, following Equation 2

$$M_{D50} = 2.138\left(M_{B50}\right)^{0.355} \quad (2)$$

(Menden-Deuer & Lessard, 2000; Polovina & Woodworth, 2012). Chl-a data came from the European Space Agency's Ocean Colour Climate Change Initiative (OC-CCI) version 3.1, which blends data from the SeaWiFS, MODIS, and VIIRS sensors into a single time series (Sathyendranath et al., 2018). SST data came from NOAA Pathfinder v5.3 (Casey, Brandon, Cornillon, & Evans, 2010; Saha et al., 2018). $M_{D50}$ was calculated for each pixel of the 4-km grid common to both the chl-a and SST data. We average $M_{D50}$ over the calendar year, to match the management time frame of this fishery, and over the spatial domain of the fishery (Woodworth-Jefcoats, Blanchard, & Drazen, 2019; Figure 1).

### 2.2 | Fisheries data

Hawaii's bigeye tuna longline fishery sets their hooks 100–400 m below the surface during the daytime (Bigelow, Musyl, Poisson, & Kleiber, 2006). In recent years, vessels set an average of 2,700 hooks per set and total fleet effort increased steadily from 20 million hooks in 2000 to 58.5 million hooks in 2018 (PIFSC, 2019b). Catch per unit effort (CPUE; number of bigeye tuna caught per 1,000 hooks set; Figure 2) was determined from vessel logbooks, which are kept by all vessel masters and include the date, time, and location of all effort set, as well as catch (in numbers) of all commercially valuable fish.
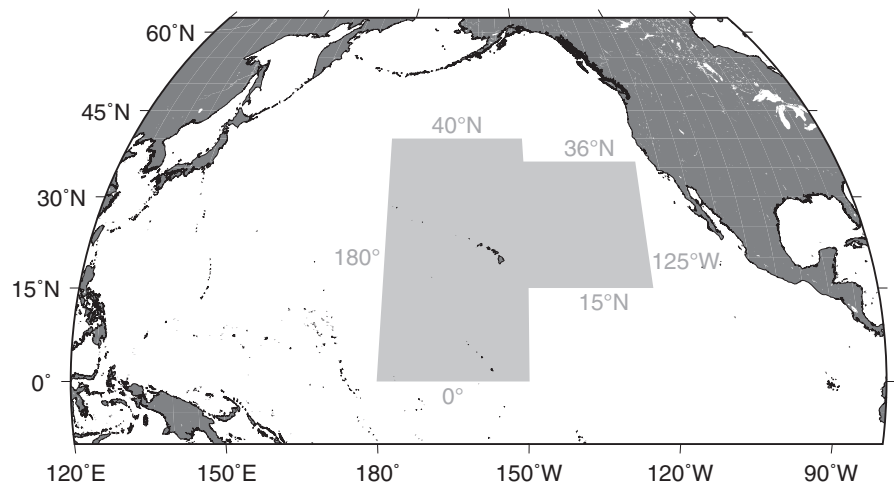


**FIGURE 1** Map showing the footprint of Hawaii's longline fishery for bigeye tuna
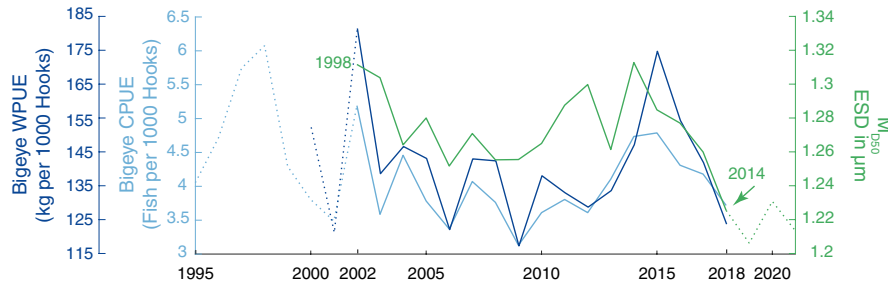
**FIGURE 2** Time series of bigeye tuna WPUE (dark blue), bigeye tuna CPUE (light blue), and 4-year-lagged $M_{D50}$ (green). Dotted lines represent years that are outside the common time period and therefore omitted from our forecast analysis (though these years were used in climatological and persistence forecasts of CPUE and WPUE) [Colour figure can be viewed at wileyonlinelibrary.com]

Logbook data are maintained by the Pacific Islands Fisheries Science Center (PIFSC; PIFSC, 2019c).

The size distributions of bigeye tuna were determined from dealer data (PIFSC, 2019a). Dealer data contain processed (gilled and gutted) weight records from all Hawaii commercial fish buyers. To obtain whole fish weights, we applied a non-linear conversion factor to the weight record (Langley, Okamoto, Williams, Miyabe, & Bigelow, 2006). Smaller fish are sometimes sold as a group and the record consists of multiple fish with a total weight for the group. In these instances, we do not know the precise weight of each fish so we attributed the mean weight to each fish in the group. We examine fish size structure by binning weights quarterly (i.e., Jan–Mar, Apr–Jun). This temporal scale matches that used in both recent bigeye tuna stock assessments (Vincent et al., 2018) as well as historical surveys (Kume, 1969).

Dealer data were also used together with logbook data to determine weight per unit effort (WPUE; Figure 2). Because not all bigeye caught are sold, to calculate WPUE for each trip, we took the mean sold weight of bigeye recorded in the dealer data and multiplied it by the number of bigeye recorded in the logbook data. We then divided

that total weight per trip by the effort from the logbook data and, finally, aggregated the WPUE by year.

## 2.3 | Forecast and evaluation

To test our hypothesis that $M_{D50}$ can be used to forecast bigeye tuna catch rates four years in advance, we evaluated the correlation between annual time series of 4-year-lagged $M_{D50}$, SST, and chl-a and both CPUE and WPUE. For significant correlations ($p < .05$), linear regressions were used to create CPUE and WPUE forecasts. The skill of these forecasts was evaluated based on two metrics: skill over climatology (i.e., long-term mean) and skill over persistence. Climatology was defined as the average CPUE or WPUE through the year prior to the forecast year (e.g., the 2005 CPUE climatology forecast value was the 1995–2004 average). Persistence was defined as the CPUE or WPUE of the previous year (e.g., the 2005 CPUE persistence forecast value was 2004 CPUE). The skill was measured by summing over the forecast period (2002–2018) the absolute values
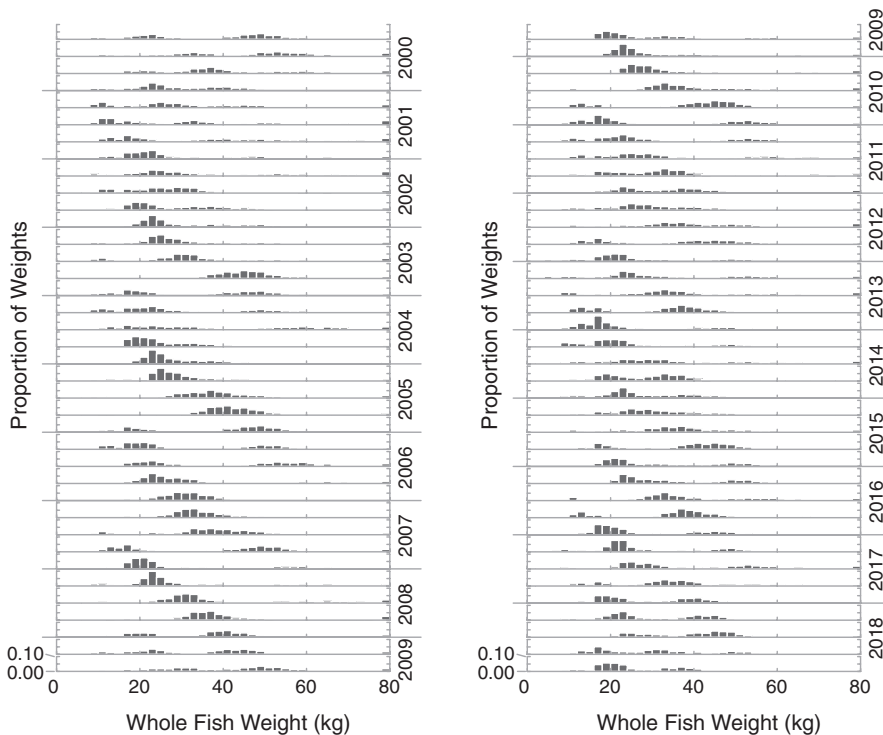


**FIGURE 3** Quarterly distribution of bigeye tuna weights. Weights ≥80 kg are grouped into a single bin

of the difference between each year's forecast and observation. Lower values indicate greater skill.

## 3 | RESULTS

The bigeye tuna caught by Hawaii's longline fleet exhibit clear cohort structure (Figure 3). Cohorts generally first appear with a minimum weight of approximately 10 kg and persist through a maximum size of near 70 kg. Individual cohorts persist for roughly two years, though the timing of their emergence and disappearance fluctuates (i.e., cohorts do not seem to exhibit distinct seasonal timing or spacing).

Annual bigeye tuna CPUE and 4-year-lagged $M_{D50}$ were correlated with a Pearson correlation coefficient, $r$, of .4828 ($p = 0.0497$; Figure 4). Annual bigeye tuna WPUE and 4-year-lagged $M_{D50}$ were correlated with $r = 0.5352$ ($p = 0.0268$; Figure 4). Correlations between 4-year-lagged SST and both CPUE and WPUE were not significant ($p = 0.0641$ and $p = 0.0562$, respectively), nor were correlations between 4-year-lagged chl-a and both CPUE and WPUE ($p = 0.0888$ and $p = 0.0637$, respectively).

We found that our forecasts of CPUE and WPUE out-performed both climatology and persistence. Skill scores for CPUE forecasts based on $M_{D50}$, climatology, and persistence were 6.9, 9.2, and 10.0 fish per 1,000 hooks, respectively. Skill scores for WPUE forecasts based on $M_{D50}$, climatology, and persistence were 184, 220, and 309 kg per 1,000 hooks, respectively.

## 4 | DISCUSSION

We found that median phytoplankton size ($M_{D50}$) is an informative predictor of bigeye tuna catch rates in Hawaii's deep-set longline fishery with a 4-year forecast window. Using variability in $M_{D50}$ proved more skillful than either climatology or persistence. Such a predictor may help the fleet time capital improvements as well as improve stock assessments for bigeye tuna and other species. Phytoplankton size has the potential to be a powerful forecasting tool because it is both fishery-independent and based on publicly available satellite data.

Our environmental predictor of bigeye tuna recruitment to Hawaii's longline fishery, $M_{D50}$, has a strong foundation in ecological theory. Hjort (1914) hypothesized that fishes' larval and juvenile life stages are the critically important stages in determining year class strength as measured by numerical abundance and that survival through these stages is determined largely by the quality of food available at first feeding. In other words, better food quality (here, $M_{D50}$) should lead to higher numbers of fish surviving through larval and juvenile phases. In turn, increased numerical abundance would be expected to lead to higher CPUE, all else being equal. Furthermore, size-based ecological theory demonstrates that ecosystems with more large phytoplankton have more large fish than ecosystems with smaller phytoplankton (Blanchard, Heneghan, Everett, Trebilco, & Richardson, 2017; Sheldon, Prakash, & Sutcliffe, 1972). This is borne out in the relationship we see between $M_{D50}$ and WPUE.

The theory underpinning our forecast centers around foraging success, which is only one piece of the survival puzzle. Larval and juvenile bigeye tuna must also avoid being preyed upon themselves. Determining larval predation rates is challenging; however, purse seine data may be able to shed light on juvenile mortality. It would be interesting, in future studies, to incorporate purse seine data into our forecast to see whether it increases skillfulness. Finer-scale spatio-temporal analyses could also reveal informative variations indicative of spawning and/or migration. To this end, knowledge of the location and timing of bigeye tuna spawning and subsequent recruitment could help further refine the forecast. While correlations with SST and chl-a were not significant, the $p$-values were quite low, suggesting the environment likely influences larval and juvenile bigeye tuna survival. The effect of interannual climate variability such as ENSO on tuna recruitment in the equatorial Pacific (e.g., Lehodey, Chai, & Hampton, 2003) highlights the likelihood that the environment influences larval survival. It might be possible to determine a better predictor by using more advanced statistical techniques, such as generalized additive models (GAMs) or polynomial fitting, that take additional environmental variables and climate indices into consideration. However, the parsimony in our method increases its utility. Fellow researchers can easily determine $M_{D50}$ over their regions and time scales of interest following the methodology presented by Barnes et al. (2011), whereas explanatory variables in GAMs would vary by region, fishery, and species of interest. Insight gained through incorporating additional fishery data, such as purse seine catch, would similarly vary. More practically, the time series of $M_{D50}$ used in our analysis could easily

**FIGURE 4** Linear regression between bigeye tuna CPUE and $M_{D50}$ (light blue) and between bigeye tuna WPUE and $M_{D50}$ (dark blue) with the 95% confidence intervals shaded, left panel. Residuals from CPUE (light blue) and WPUE (dark blue) predicted from linear regression, right panel [Colour figure can be viewed at wileyonlinelibrary.com]
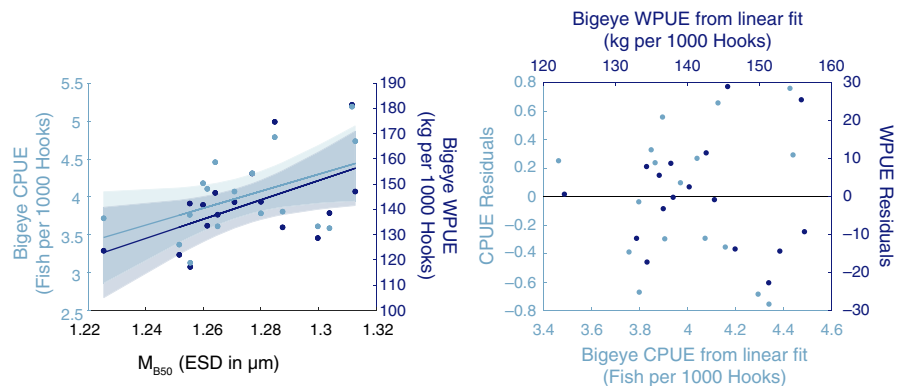
be made available to both regional fishery managers and the fishing industry (sensu Howell, Kobayashi, Parker, Balasz, & Polovina, 2008). While results from more detailed analyses could also be made available, they would likely be harder to communicate.

We find the ability of $M_{D50}$ to forecast WPUE particularly encouraging given that this fishery is managed based on an annual tonnage quota. In recent years, regional quotas have been met increasingly early in the year, and recent studies of Hawaii's longline fishery suggest that the fishery is overcapitalized (Ayers, Hospital, & Boggs, 2018). The ability to forecast when the regional quota is likely to be reached earlier or later in the year could allow individual fishers to better time their trips (e.g., Hobday, Spillman, Eveson, & Hartog, 2016) or help the industry take collective action to optimize effort. Collective industry action could be particularly effective given that total annual catch and the timing of reaching regional quotas are strongly driven by total fishing effort (PIFSC, 2019b). Our forecast also provides a mechanism by which scenarios for management strategy evaluations could be crafted. For example, the status quo could be tested alongside scenarios with annual quotas that fluctuate in response to $M_{D50}$-based forecasts of relative fish abundance. These alternative strategies could then be evaluated for their effect on both stock status and fishery yield (Tommasi et al., 2017). Recent work has shown that including environmental covariates such as $M_{D50}$ in stock assessments may reduce recruitment uncertainty (Sculley, Ijimi, & Chang, 2018). Such an improvement would be particularly beneficial for bigeye tuna assessments given the species' commercial importance and questionable stock status.

Factors, such as fleet (Woodworth-Jefcoats, Polovina, & Drazen, 2018) and market dynamics, regulations (Ayers et al., 2018), and the environment (e.g., Bograd et al., 2019) will always limit how well fishery performance can be forecast. That said, we show that it is possible to forecast catch rates of bigeye tuna with some skill using publicly available, fishery-independent data. We also present a mechanism that could move us closer to finding an environmental predictor of tuna recruitment and implementing adaptive and ecosystem-based regional fishery management.

## CONFLICT OF INTERESTS
The authors declare that their research was conducted without potential conflicts of interest.

## AUTHOR CONTRIBUTIONS
PW conceived the study. PW and JW designed the study, analyzed and interpreted the data, wrote the manuscript, and approved the final version for publication.

## ETHICAL APPROVAL
The authors confirm that this research was conducted pursuant to relevant ethical guidelines. No human or animal subjects were used in this study.

## DATA AVAILABILITY STATEMENT
Satellite data used in this study can be obtained from NOAA's OceanWatch at https://oceanwatch.pifsc.noaa.gov/erddap/griddap/esa-cci-chla-monthly.html (chlorophyll-a) and https://oceanwatch.pifsc.noaa.gov/erddap/griddap/pf5-3-monthly.html (sea surface temperature). Fisheries data used in this paper are subject to confidentiality of information requirements under the Magnuson–Stevens Fishery Conservation and Management Act (Magnuson–Stevens Act or MSA) and are not available to the public except in summary aggregate form. Information on requesting access to these data can be found at https://inport.nmfs.noaa.gov/inport/item/2721 (logbook data) and https://inport.nmfs.noaa.gov/inport/item/5610 (dealer data). All information graphed or tabulated in this paper are non-confidential and are available from the authors upon request.

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