Modeling Tools to Help Assess the Distribution of Priority Reef Fish Species for Jurisdictional Coral Reef Fishery Management Plans in Guam

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Cover: An assemblage of reef fish swim over a coral reef near Gab Gab Beach, Guam
Photo credit: Ari Halperin, NOAA Fisheries

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Executive Summary

Reef fishes play a vital role in supporting local fisheries and providing essential ecosystem services, particularly for maintaining the health of coral reefs. In Guam, shore-based fishing methods contribute significantly to the local fisheries catch for cultural, recreational, and economic benefits. Understanding the distribution of reef fish species is therefore crucial for effective fisheries management and would inform the ongoing effort by the Government of Guam to develop Guam's Jurisdictional Coral Reef Fisheries Management Plan (JCR-FMP). This effort requires consideration of environmental factors such as temperature and reef substrate, and human influences such as fishing pressure and water quality. To assess the distribution of priority reef fish species around Guam, we analyzed five years of fish survey data from the National Coral Reef Monitoring Program (2009–2022) using various spatial modeling techniques. By integrating satellite and in situ measurements, we further investigated the environmental and human-driven factors influencing species distributions. This comprehensive study enhances our understanding of species distribution patterns at the sub-island scale, enabling more substantiated predictions of fish biomass based on key drivers like fishing pressure and coral reef calcifier cover. The findings from this work also bolster evidence-based decision making to inform the broader goals of Guam's JCR-FMP.

Introduction

Reef fishes are a critical component of local fisheries for Pacific island communities, serving as a cornerstone for sustenance, cultural practices, and economic well-being. Additionally, these fishes play a pivotal role in maintaining the health of coral reefs by providing essential ecosystem services such as herbivory (Holmlund & Hammer, 1999). Guam stands as a noteworthy example of a region where shore-based fishing practices, encompassing hook and line, netting, and spearfishing, contribute significantly to the local fisheries catch (Hensley & Sherwood, 1993).

The interactions that shape the ecology of reef fishes in a particular area involve complex factors such as local environment and human impacts. Variables like sea surface temperature (SST), primary productivity, fishing pressure, runoff and effluent, plus the establishment of marine protected areas (MPAs) or military zones collectively influence the abundance of these marine resources.

A critical initial step in effective local reef fisheries management is gaining a comprehensive knowledge of the distributions and drivers of target species biomass in a changing ecosystem. This information requires identifying spatial patterns and quantifying the multifaceted drivers shaping these distributions, encompassing both environmental variables and human influences. An improved understanding of these fish-environment associations can pave the way for more precise predictions of essential fish habitat and provide insight about how changing conditions such as temperature, fishing pressure, or coral reef cover may influence the distributions of various species.

This study evaluates the biomass and distributions of priority reef fish species around Guam using advanced statistical and machine learning techniques and environmental data analysis tools. These spatial modeling approaches allow us to evaluate reef fish dynamics at intra- and inter- island scales and how these dynamics are shaped by the surrounding environment. We combine five years of fish survey data spanning 2009 through 2022 with gridded satellite and in situ environmental measurements to explore species-specific spatial biomass patterns and the various factors influencing species distributions around Guam. Our study further leverages the Environmental Data Summary (EDS), an advanced tool created by scientists at the NOAA Pacific Islands Fisheries Science Center (PIFSC), to analyze changes in baseline environmental conditions in Guam and the Commonwealth of the Northern Mariana Islands (CNMI).

In addition to local and regional environmental factors, the assessment and management of reef fish species in Guam are guided by federal and jurisdictional mandates, including the priorities of the National Oceanic and Atmospheric

Administration National Marine Fisheries Services (NOAA NMFS). Agency mandates emphasize the need for science-based decision-making and the sustainable management of fisheries resources. By integrating scientific data and advanced modeling techniques, such as the statistical and machine learning approaches employed in this study, managers and policymakers can make informed choices to maintain healthy fish populations and protect the marine environment.

The findings from this research contribute to the broader goals of the NOAA NMFS and the Government of Guam's development of its Jurisdictional Coral Reef Fisheries Management Plan (JCR-FMP) by providing valuable information on the distribution and drivers of reef fish species in Guam. This knowledge can support evidence-based decision-making, aid in the development of effective management strategies, and ultimately contribute to the sustainable utilization and conservation of Guam's marine resources in alignment with the Guam JCR-FMP.

Materials and Methods

Study area: Guam

Located in the tropical North Pacific Ocean, Guam sits at the very southern end of the Mariana Islands Archipelago, encompassing an area of 208,234.15 km^2 (Figure 1). As the most populated of these islands, Guam is currently home to 169,330 people (U.S. Census Bureau, 2021) and is the only Mariana Island that is a territory of the United States. Shore-based and small boat fishing within the region targets many coral reef species near shore, as well as both pelagic and bottom fish species further offshore. The coral reefs around Guam contribute significantly to the local economy through tourism and ecosystem services, with an annual worth of U.S. $127 million (Van Beukering et al., 2007).

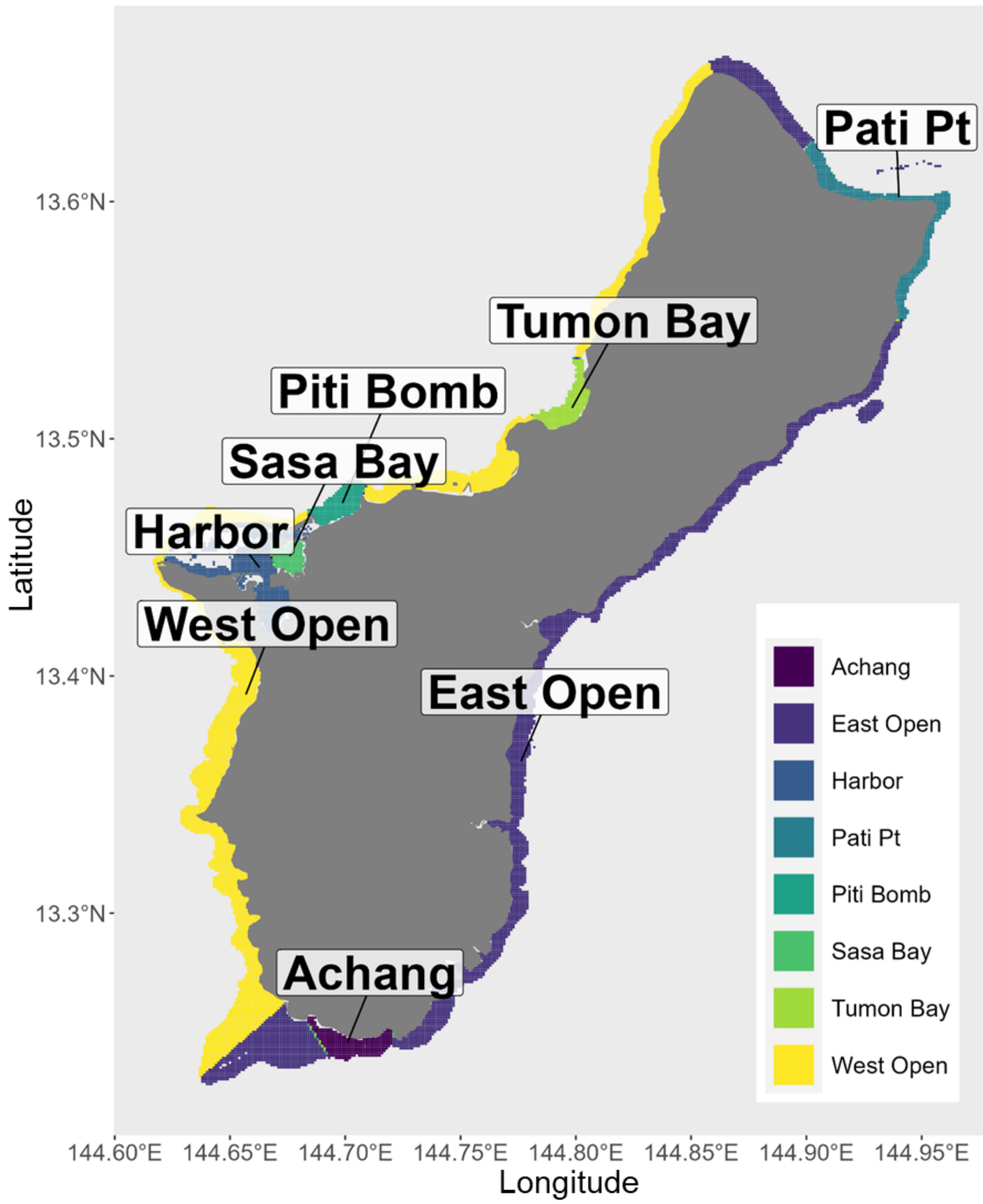

Figure 1. Map depicting the island of Guam and its NOAA NCRMP survey sectors, which include the major Marine Protected Areas (Pati Point, Tumon Bay, Piti Bomb Holes, Sasa Bay, and Achang).

Satellite-based analysis of changes in reef environment baseline conditions

Environmental Data Summary (EDS) was used to analyze changes in baseline environmental conditions in Guam and the CNMI. The EDS tool gives users a simple, consistent way to enhance in situ survey data using external environmental data. EDS allows users to download, filter, extract, and summarize large amounts of gridded and tabular data given user-defined time stamps and geographical coordinates. The various external environmental data summarized at individual survey sites can help scientists assess and understand how living marine resources are impacted by environmental variabilities. EDS is written in the open-source programming language R and provides users with an interface to NOAA CoastWatch and OceanWatch data sets through the Environmental Research Division Data Access Program (ERDDAP) server protocol. The environmental variables chosen in this analysis include sea surface temperature (SST) and chlorophyll-a concentration (chl-*a*; Table 1). Gridded SST data were gathered from the NOAA Daily Global 5-km Geo-Polar Blended Sea Surface Temperature Analysis (v1.0), which provided daily SST with a resolution of 0.05°. Daily surface chl-*a* concentrations were available from ESA OC CCI v5.0 at ~0.05° resolution. The selection of environmental variables for this analysis was guided by their relevance to the JCR-FMP. To provide a comprehensive overview of these environmental conditions, the outputs from EDS were aggregated across the Guam and inter CNMI islands, which are encompassed by the National Coral Reef Monitoring Program (NCRMP) survey within the Mariana Islands region.

Table 1. Description of environmental variables included in the JCR-FMP environmental baseline analysis. ESA OC CCI: European Space Agency Ocean Colour Climate Change Initiative.

Data set	Description	Period	Unit
NOAA Geo-Polar Blended SST Analysis	Sea-surface temperature	1984–present	°C
Chlorophyll-*a* ESA OC CCI	Sea-surface chlorophyll concentration	1997–present	mg m^{-3}

Data collection: Fishery-independent reef fish surveys

Reliable estimates of reef fish biomass and their spatial distributions at broad scales can be derived from fishery-independent surveys. Our study area encompasses the shallow (0–30 meters (m)) forereef habitats around Guam (Figure 2). The density observations for priority reef fish species were collected in situ as part of the NCRMP's stratified random stationary point count (SPC) surveys, conducted by PIFSC.

The fishery-independent surveys are based on a stratified random sampling design using the paired-diver SPC method (Ayotte et al., 2015; Heenan et al., 2017; McCoy et al., 2019; NCEI Accession 0157596, 0274016, 0157592, 0157633, 0157633, 0166381) and were carried out during daylight hours. Spanning over a decade (2009–2022), these statistically randomized surveys covered approximately 421 survey locations around Guam. Detailed descriptions of these data sets are provided in Heenan et al. (2017), McCoy et al. (2019), and Suarez & Grabowski (2021). In summary, divers recorded fish species, size (nearest centimeter (cm)), and abundance in visually estimated paired stationary 15-m diameter survey cylinders (353 m^2) extending from the seafloor to the surface using a marked transect line as a reference for estimating cylinder extent. These surveys yielded site-level biomass records for a variety of fish species and functional groups. Though conducted from April to December, the primary survey period was June to October.

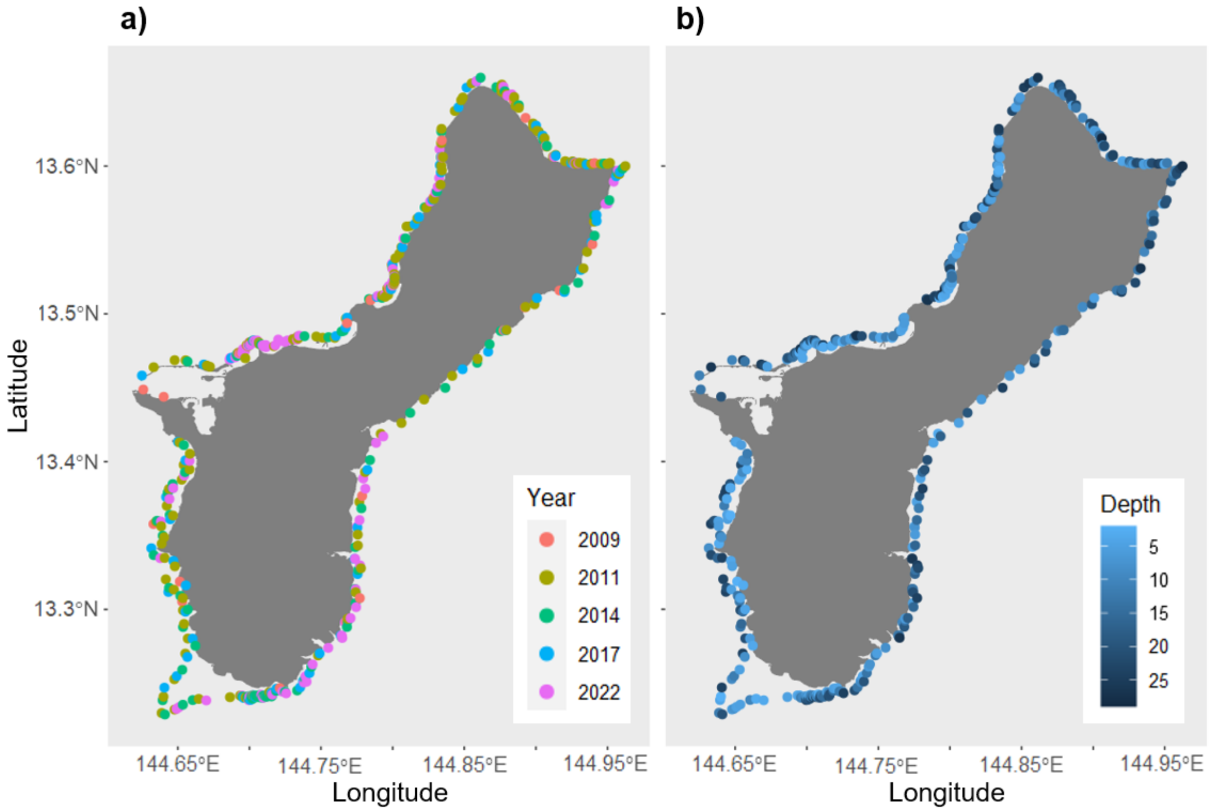

Figure 2. Maps of NCRMP reef fish survey sites across Guam by (a) year and (b) depth (m). Fish surveys spanned five separate sampling occasions between 2009 and 2022.

Enhancing jurisdictional coral reef fishery management plans through modeling approaches

Where are the fish?

We used a spatiotemporal model to examine how the biomass of priority reef fish species is distributed across Guam's nearshore habitats. This approach can merge a spatially explicit temporal trend (local trend) with spatial (temporally constant) and spatiotemporal (time-varying) elements. Here, each priority reef fish species' biomass was modeled using both 'fixed' effects (i.e., depth) and 'latent' spatial effects derived from Gaussian Markov random fields. Accounting for spatial correlation among nearby spatially referenced observations and their temporal proximity allows for biogeographical insights into species habitat preferences within shallow waters. We used a statistical mixed-model approach called a generalized additive mixed-effect model (GAMM). This method largely deals with spatial links between observations and can consider additional environmental factors. However, we did not include dynamic environmental variables in these models because the complex spatial random fields accounted for nearly all of the biomass variance for each species. Thus, the objective of these models was primarily to answer the question, "where are the fish?" in terms of island spatial patterns and depth preferences. Our modeling included all size categories and age classes combined because these species have low biomass in Guam's shallow waters. The R *sdmTMB* package (Anderson et al., 2022), known for its flexibility and automatic differentiation capabilities, was utilized for fitting a comprehensive GAMM incorporating a local trend to compute size-aggregated biomass. Although the *sdmTMB* package accommodates spatial and spatiotemporal aspects, our focus was solely on the spatial component. We added the year as a factor, allowing us to estimate average biomass for each year. Given that the biomass data encompasses both zero and positive values, a Tweedie distribution model with a log link was employed. Model performance was evaluated through internal cross validation, primarily by assessing the variability of log likelihoods of left-out data returned from 5-fold cross validation splits of the data. Models that resulted in highly variable log likelihoods between folds were excluded from the study. This comprehensive analytical approach provided insights into biomass distribution changes of priority reef fish species with space and depth in the shallow waters surrounding Guam. From these model results, we compare model-based estimates with survey observations and present maps of normalized biomass estimates for each species.

Why are fish distributed as they are?

To address this question, we evaluated the relative influences of environmental and anthropogenic variables (Table 3) on the distribution of reef fish species using boosted regression trees (BRT; the *gbm* package in R; Greenwell et al., 2022), an ensemble machine learning method for species distribution modeling. BRTs are a conglomeration of many decision trees, and each additional iteration improves predictions from the worst fit data in the previous tree. BRTs can deal with missing predictor variable data, a moderate amount of predictor collinearity, and can be used to model complex non-linear relationships and predictor interactions (Elith et al., 2008). The structure of each BRT is described in Table 2. Machine learning approaches like BRTs have advantages and disadvantages. While they can often outperform more common statistical methods, they are susceptible to overfitting that can lead to unstable response curve shapes and attribute variable importance to noise. However, we mitigated these potential overfitting scenarios by (1) using smooth averaged response curves from a double ensemble approach (i.e., 100 model ensembles of each decision tree ensemble) and (2) including a random normal variable in the model ensembles as a threshold below which to omit noisy variables. This approach enabled us to explore the influences of many potential drivers of reef fish biomass distribution around Guam.

Table 2. Model structure of Boosted Regression Trees (BRT).

Model Component	Definition	Value
Cross validation split	Proportion of data set used for training and proportion of data left out for validating	75–25
Ensemble iterations	Total number of 75–25 split models in BRT ensemble. Additional layer of randomness.	100
Number of folds (k)	To determine the optimal number of trees in each model, the training set is divided into k-folds. K-1 (9) folds are used for training and the remaining fold is used for validating in each iteration.	10
Bag fraction	Proportion of data selected to fit trees at each step	0.6
Tree complexity	'Depth' of interactions within the model	3
Learning rate	Relative contribution of each additional tree	0.001

To capture stronger gradients of environmental and human impact variables and evaluate their influences on species distributions, we expanded the spatial domain of our models to include all of the southern Mariana Islands (Guam, Rota, Tinian, Aguijan, and Saipan). Gridded predictor variables (i.e., satellite oceanographic measurements and human population density) were matched with fish survey data and temporally summarized using EDS, and benthic habitat predictor variables (e.g., coral and crustose coralline algae "calcifier" cover) were measured in situ at each fish survey location (NCRMP Tier1 site-level benthic cover data). We selected predictor variables based on hypotheses regarding their relevance to reef fish occurrence distributions and set a predictor collinearity cutoff of 0.7 (Table 3). This approach allowed us to test hypotheses of the different timescales of certain variables that may be more or less relevant to species distributions, and using BRTs maximized the number of semi-collinear variables that we could include in the models. The percent contribution of each predictor variable is a measure of how often it is used for tree splitting, weighted by the extent to which the predictor improves model fit. Only predictors with importance greater than random noise were retained in the final model. We used the area under the receiver operating characteristic curve (AUC), a metric that reflects the probability of a randomly selected positive outcome being correctly ranked, to determine the 'goodness' of each model

(Bradley, 1997). Only models with an AUC greater than 0.7 were considered passable (Hosmer & Lemeshow, 2013; Mandrekar, 2010). We present two AUC scores for each model—AUC1 reflects how well the model predicted new data (i.e., the 'test' sets), and AUC2 reflects how well the model predicted over all observations. We present examples of predicted probability of occurrence (prob. occur) for two priority species, M. grandoculis and A. lineatus. These species were selected as case studies based on stronger confidence in their model outputs and the predicted importance of human pressures and reef cover to their distribution.

Table 3.Environmental and human impact variables included in boosted regression tree models (BRT). Grey indicates variables that were ultimately excluded due to predictor collinearity cutoff (0.7). SST, chlorophyll-a (productivity proxy), and Kd490 (turbidity proxy) were temporally summarized using the environmental data summary tool (EDS). Gray variables were ultimately excluded from models due to high collinearity (r > 0.7).

Predictor	Statistic	Temporal	Spatial	Source	Reason for including
Depth (m)	--	--	At survey site	NCRMP survey	Depth constraints/preferences
Rugosity (m) (Rugosity_30m)	--	--	30 m (3×3 @ 10m)	Pacific Islands Benthic Habitat Mapping Center	Habitat complexity
Calcifier Cover (CCA_Coral)	% cover	--	At survey site	NCRMP survey	Available reef building habitat; structure
Macroalgae	% cover	--	At survey site	NCRMP survey	Reef health indicator (>macroalgae means <healthy reef)
Sediment	% cover	--	At survey site	NCRMP survey	>sediment is indication of edge habitat
Year	--	--	--	NCRMP survey	Inter-annual variability
Pop. density (Pop_15km)	mean	Climatology (2010 or 2020)	3 km averaged per 15 km around sites	Gridded population of the world v4	Human presence, broad/rough proxy for fishing pressure in the absence of fishing data

Predictor	Statistic	Temporal	Spatial	Source	Reason for including
SST	Mean	1 day	~5 km	Coral Reef Watch	Suitability on day of observation; likely to influence more mobile species
	Mean	1 month			Influence of seasonal temperatures
	Mean	1 year			General survivability/habitat suitability of area (species with short life span or that can move to a different area)
	Q05	1 month			Influence of recent cold event
	Q05	1 year			Lower thermal limit of the area
	Q95	1 month			Influence of recent heatwave or rapid seasonal shift
	Q95	1 year			Potential heat event in the previous year (could also have effect on habitat) or upper thermal limit over past year
	Max monthly Mean	Climatology (1985-2012)	~5 km	Coral Reef Watch	Upper thermal limit of the area (always occurs during summer months)
Chlorophyll-a	Mean	1 year	~4 km	European Space Agency Ocean Color Climate Change Initiative	General productivity/human pollution influence of the area
	SD	1 month			Recent effluent discharge or outflow event
Kd490	Mean	1 year	~4 km	European Space Agency	General turbidity of the area

Predictor	Statistic	Temporal	Spatial	Source	Reason for including
	SD	1 month		Ocean Color Climate Change Initiative	Recent river outflow or sedimentation event

Analyzing predicted occurrence changes

We used ensemble BRT models to examine how predicted occurrence changes in response to shifts in important variables such as calcifier cover and population density. To do so, we first generated a 300-m prediction grid using NOAA National Geophysical Data Center bathymetry data for the 0 through 30 m depth waters around Guam, along with the corresponding environmental variables and population density. These variables were selected from the date closest to the most recent NCRMP fish surveys around Guam (2022-08-10) to ensure the most up to date predictions. We processed the gridded prediction field through EDS to pair each cell with environmental variables and population density. For benthic habitat variables (e.g., calcifier cover, macroalgae, and sediment), we used nonlinear spatial interpolation to pair the NCRMP Tier1 site-level benthic cover data using GAMs and Kriging interpolation with each grid cell. Using the gridded prediction field with matched environmental and human impact variables, we analyzed changes in modeled species occurrence for two case study priority species, *A. lineatus* and *M. grandoculis*.

Using the modeled species occurrence under "present conditions" as a baseline, we explored how simulated changes in key predictor variables, specifically population density and calcifier cover, might influence the distribution of these species. This process assumed 5 or 10% increases or decreases in these predictors at each grid cell from the most recent NCRMP survey dates. With these changes, we re-predicted species occurrences across the Guam shallow waters and highlighted any deviations from the modeled occurrences under “present” conditions.

Species grouping

While it is highly informative to model the occurrence and distributions of individual reef fish species, many priority species were too sparse in the survey data set so could not be evaluated by these methods. Therefore, we present grouping as an alternative example of how modeling efforts can incorporate and provide insight on those rarer species. There are numerous grouping factors that can determine how similar species might be evaluated together, such as functional roles (Tebbett et al., 2022), importance to fisheries (Houk & Starmer, 2010), body size (Hawaiʻi Fishing Regulations, 2022), and prime spawners (Froese & Pauly, 2000; Randall, 2007). Recent efforts in Maui have focused a combination of fisheries importance and body size to group some reef fish species and have also been building regulations for scarids (parrotfishes), a heavily fished group.

We present a similar example of how this grouping could be used to generate species-complex distribution models and maps for Guam. By combining observations for all large (max. size > 50 cm) and small (max. size < 50 cm) parrotfishes found in the southern Mariana Islands, we used BRT models to identify key variables influencing the occurrence of these groups and mapped their probability of occurrence around Guam following the same methods described above. Maximum sizes of each species were determined through FishBase and we ultimately identified 14 large species and 14 small species of parrotfishes within the southern Mariana Islands from NCRMP fish surveys (Table A1).

Results

Changes in local fisheries' environmental baseline conditions at regional scales

The satellite-based assessment of changes in reef environment baseline conditions shows shifts in several baseline environmental variables, which may have implications for reef fish habitat and local fisheries in Guam (Figure 3). Over recent decades, reef fish habitats around Guam have experienced an increase in sea surface temperatures (SST) at a rate of 0.02417 ºC per year. Additionally, a decline in chlorophyll-a concentrations, an indicator of primary productivity, has been observed at a rate of -0.00033 milligrams (mg) m^{-3} per year. These changes were consistent across all seasons and calendar months.

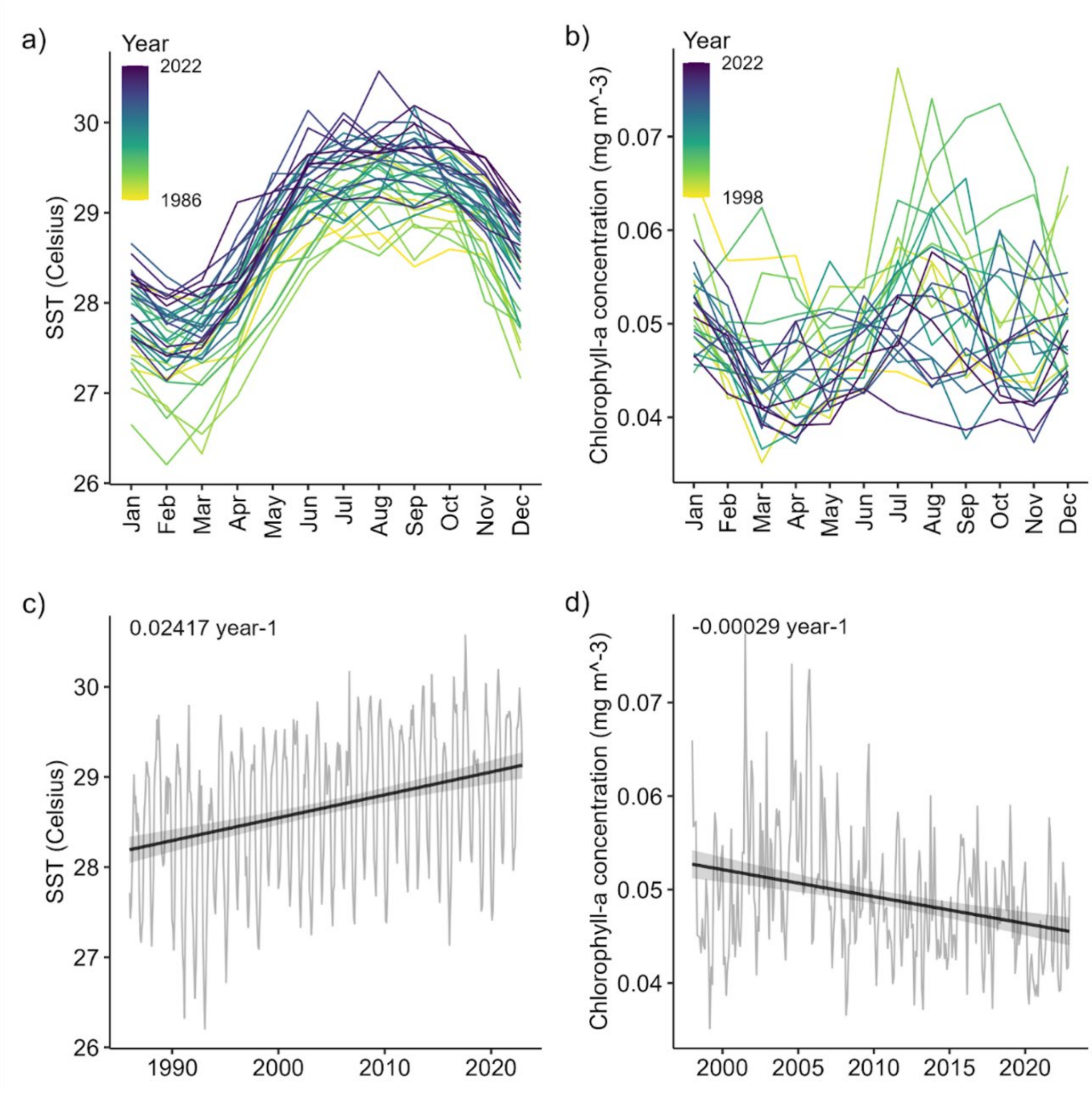

Figure 3. Seasonal and long-term trends of environmental variables relevant to Guam's local fisheries' baseline conditions derived from the Environmental Data Summary. Panels (a) and (b) illustrate the annual sea surface temperature (SST) and chlorophyll-a concentration (Chla) cycles. Each line represents the monthly average SST and Chla for a given year. The color gradation from purple to yellow marks the years from earliest to most recent, visualizing temporal progression. The bottom panels (c) and (d) depict the overall trend from 1986 to 2022 for SST and 1998 to 2022 for Chla.,The grey lines indicate variability, and the solid black lines represent the trend in SST at a rate of 0.02417 °C year^{-1} and Chla at a rate of -0.00029 mg m^{-3} year^{-1}.

Priority reef fish survey data

We analyzed five years of NCRMP fish survey data from Guam spanning 2009-2022 that included 421 unique survey locations. Using a minimum observation threshold of 5% frequency of occurrence (%FO) in the survey data set, five priority reef fish species (*Kyphosus sp., Epinephelus merra, Lethrinus olivaceus, Cheilinus undulatus, Bolbometopon muricatum*) fell short of this threshold and thus lacked sufficient observations to generate model-based biomass estimates (Table 3). Two additional species (*Lutjanus fulvus* and *Chlorurus frontalis*) were omitted from the study as they likewise lacked enough observations to meet model diagnostic standards (e.g., the log likelihoods were highly variable between folds in the cross validation). Ultimately, we were able to generate model-based biomass indices for five priority reef fish species: *Acanthurus lineatus* (hiyok; striped surgeonfish), *Naso literatus* (hangon; orangespine surgeonfish) , *Caranx melampygus* (tarakitu; bluefin trevally), *Scarus schlegeli* (magaham; yellowband parrotfish), and *Monotaxis grandoculis* (matan hagon; big eye emperor).

Table 4. Reef fish species identified as priorities for Jurisdictional Coral Reef Fisheries Management Plan (JCR-FMP) development in Guam. Chamorro names for each species are followed by Latin names in parentheses. %FO indicates the frequency of occurrence of given species in the NCRMP fish survey data set. Fishing methods indicate the known methods or gear used to catch a given species (Gerry Davis, pers. comm). Model indicates whether or not there were enough occurrences of a given species to derive model-based indices of biomass.

Species	**%FO**	**Fishing methods**	**Model**
Hiyok (*Acanthurus lineatus*)	17%	spear	Yes
Hangon (*Naso lituratus*)	81%	spear, surround/gill net	Yes
Tarakitu (*Caranx melampygus*)	20%	cast/surround net	Yes
Laggua (*Scarus schlegeli*)	36%	spear	Yes
Matan hagon (*Monotaxis grandoculis*)	25%	spear, line	Yes
Guili (*Kyphosus sp.*)	3%	spear, line	No
Bu‘a (*Lutjanus fulvus*)	11%	spear, line	No
Magaham(*Chlorurus frontalis*)	6%	spear, gill net	No
Gådao (*Epinephelus merra*)	3%	spear, line	No
Lililok (*Lethrinus olivaceus*)	4%	spear, line,	No
Tangison (*Cheilinus undulatus*)	4%	spear, line	No
Atuhong (*Bolbometopon muricatum*)	0%	spear	No

Model-based biomass estimates of priority species around Guam

Spatial GAMMs provide insight into relative biomass patterns of priority species

Overall, biomass predictions for all five species were fairly consistent though slightly lower than observations at the island sector level (Figure 4). Pati Point and Tumon Bay often showed higher observed and predicted biomass than other sectors; Pati Point showed particularly high biomass for *N. literatus* and *C. melampygus* (Figure 4b,c) and Tumon Bay showed particularly high biomass for *A. lineatus* and *M. grandoculis* (Figure 4a,e). Piti Bomb Holes had the highest biomass for *S. schlegeli* (Figure 4d). The harbor had low biomass for several species, with the biggest discrepancy between observed and predicted biomass for *N. lineatus* and *M. grandoculis* (Figure 4b,e). Limited sampling efforts in the harbor may have contributed to the lower biomass estimates for several species, as well as to the limited model skill in accurately predicting biomass within this specific sector.

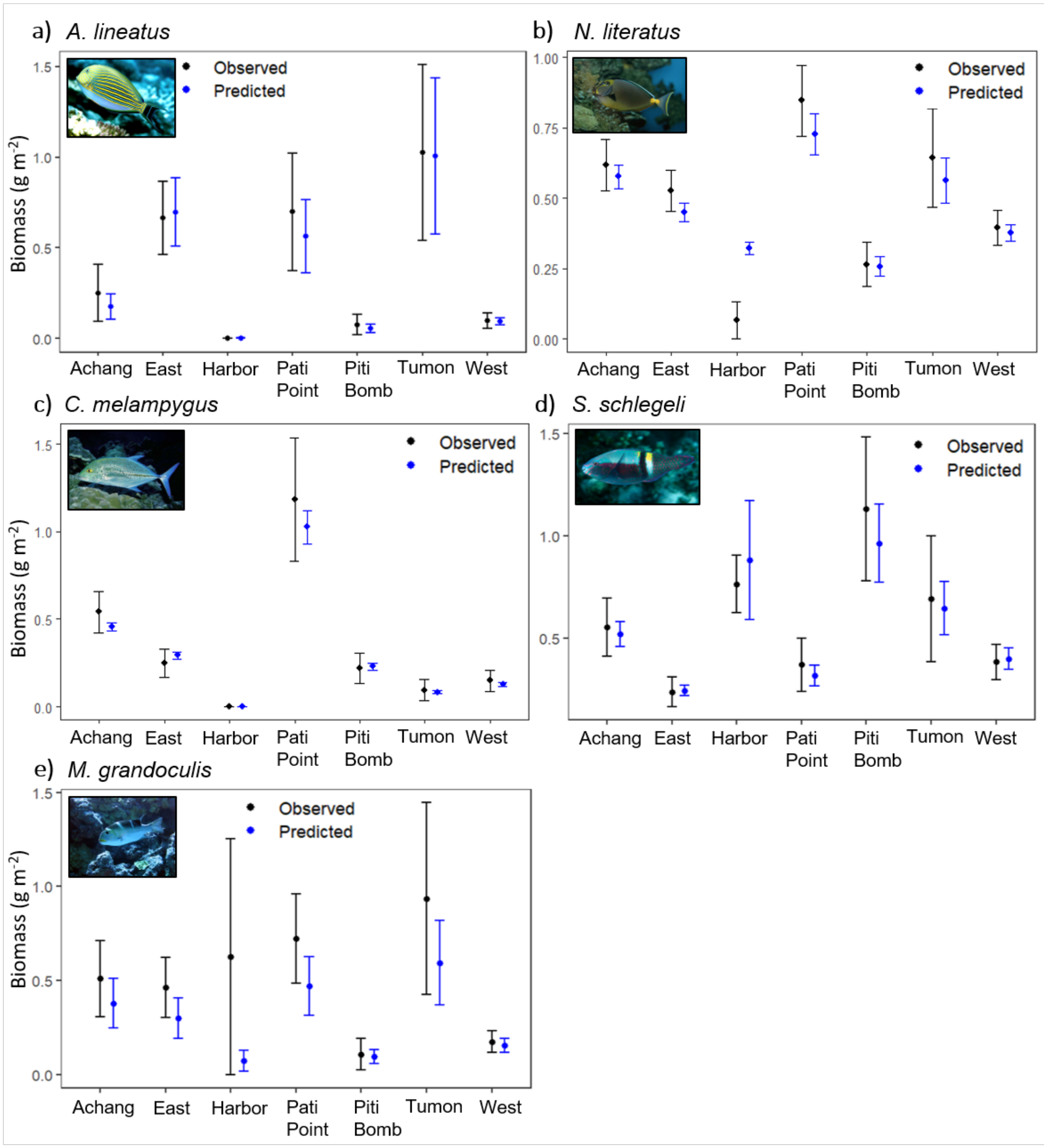

Figure 4. Observed (black) and spatial GAMM-predicted (blue) biomass (± SE) of priority reef fish species across each island sector of Guam. (a) *A. lineatus,* (b) *N. literatus*, (c) *C. melampygus*, (d) *S. schlegeli*, and (e) *M. grandoculis*. Achang, Pati Point, Piti Bomb, and Tumon are marine preserves. Note the slightly different y-axis scales.The spatial GAMMs indicated clear depth associations for four out of the five species we evaluated. Modeled depth trends for *A. lineatus* suggested that nearly all biomass for this species resides above 5 m (Figure 5a). *N. literatus, S. schlegeli,* and *M. grandoculis* all had positive

modeled depth trends. *N. literatus* biomass was present at all depths but reached a maximum around 15 m (Figure 5b), while *S. schlegeli* and *M. grandoculis* showed nearly no biomass present shallower than 5 m and 10 m, respectively (Figure 5d, e). There were no clear modeled depth trends for *C. melampygus* (Figure 5c).

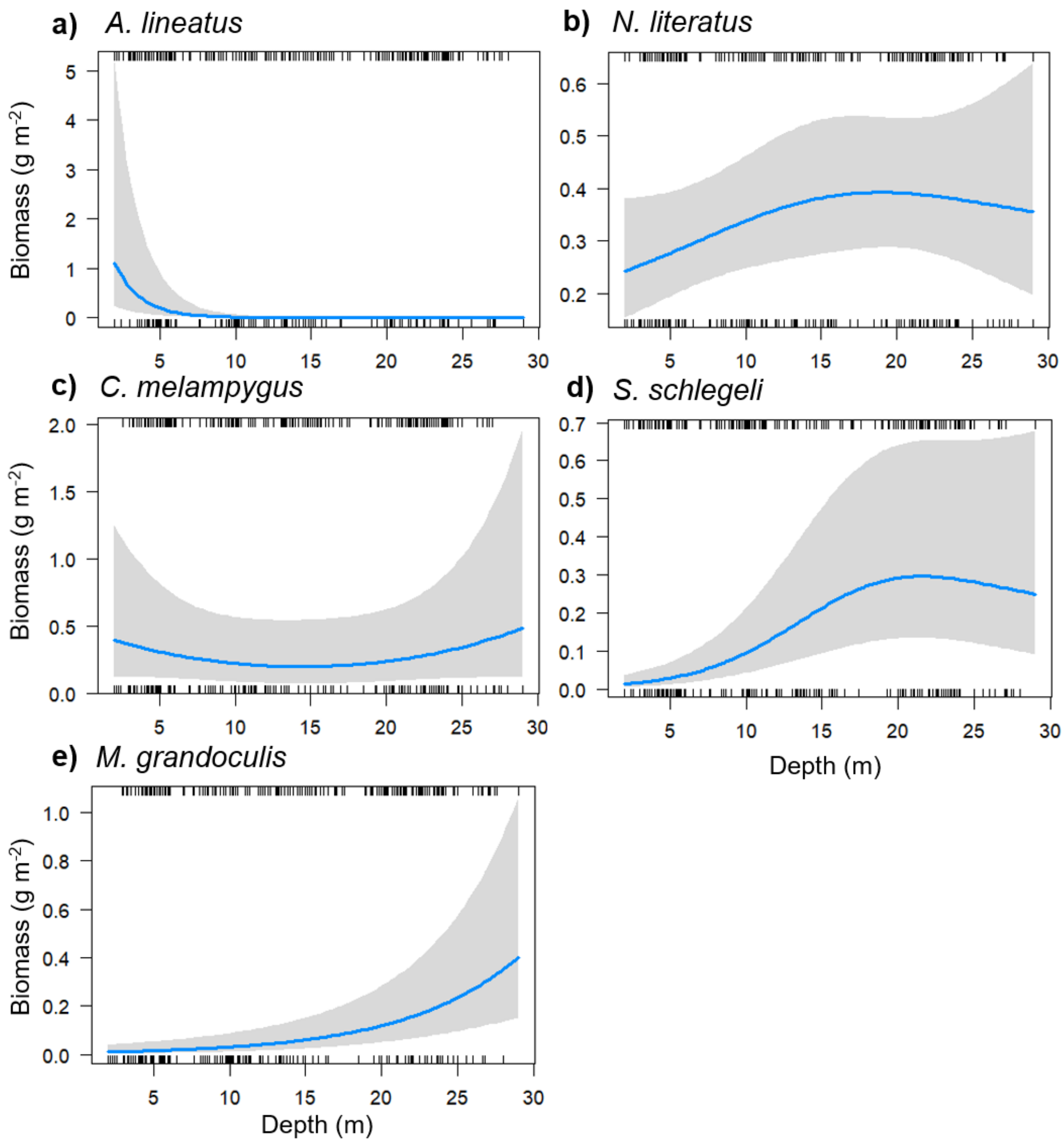

Figure 5. Modeled depth trends of reef fish biomass for five priority species. (a) *A. lineatus,* (b) *N. literatus*, (c) *C. melampygus,* (d) *S. schlegeli*, and (e) *M. grandoculis*. Blue lines indicate trend and grey bars show 95% confidence intervals. Black tick marks show sample distributions across depths.Predicted biomass trends for the 0 to 30 m depth range around Guam varied considerably among priority reef fish species. *A. lineatus* was predicted to have

the highest biomass in the eastern sector at shallow depths and relatively low biomass across the rest of the island (Figure 6a). *Naso literatus* was predicted biomass is spread more evenly around the island, with hotspots around Pati Point, Tumon Bay, and the eastern sector (Figure 6b). *C. melampygus* biomass predictions were highest around Pati Point with no clear depth trend (Figure 6c). *S. schlegeli* was predicted to have higher biomass at deeper depths around the western sector, harbor, and southern end of the island (Figure 6d). *M. grandoculis* biomass was likewise predicted to be higher at deeper depths with hotspots in Tumon Bay, Pati Point, and the southern end of the island (Figure 6e).

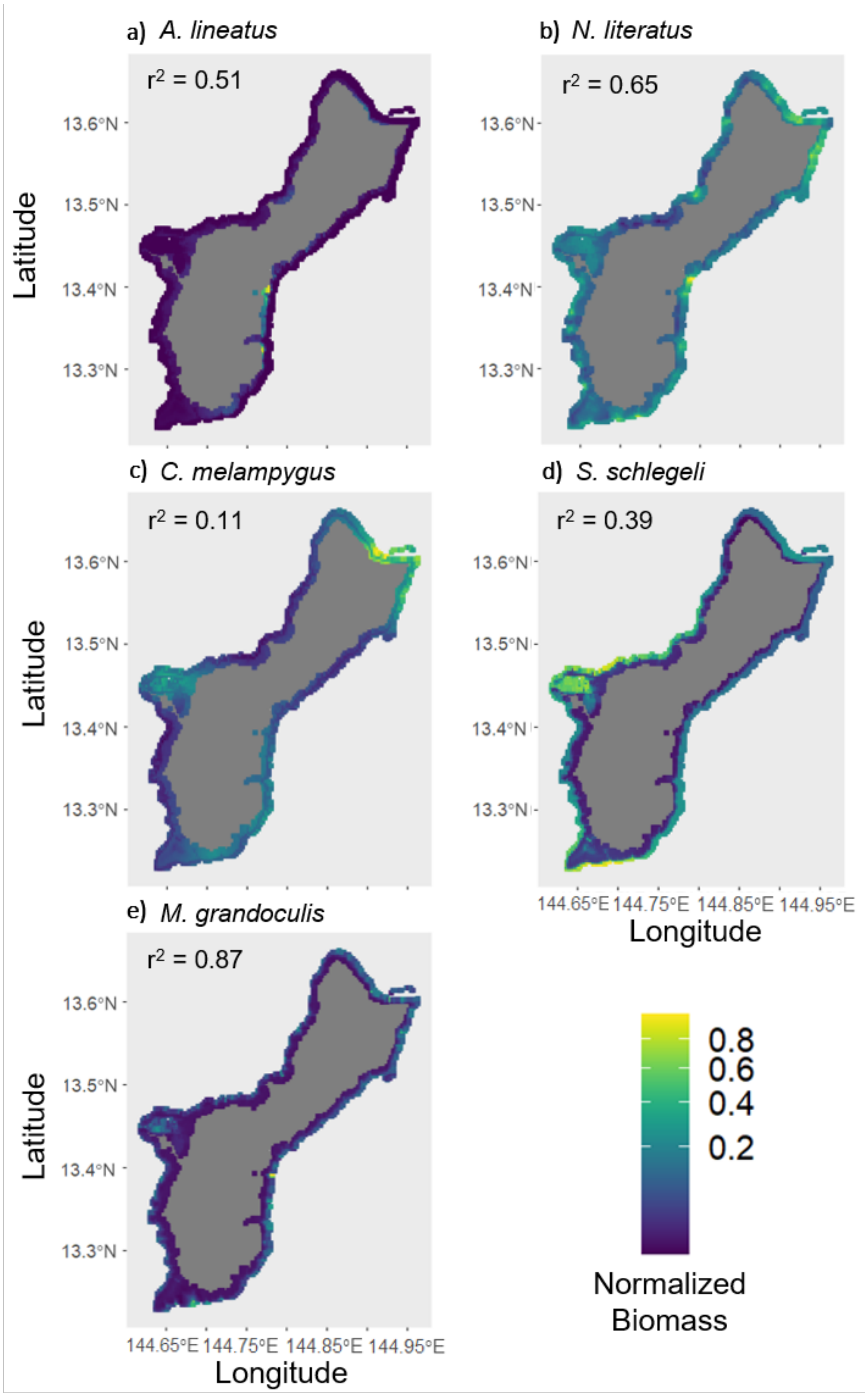

Figure 6. Maps of normalized predicted biomass for five priority reef fish species within 0-30 m depth around Guam. (a) *A. lineatus,* (b) *N. literatus*, (c) *C. melampygus,* (d) *S. schlegeli*, and (e) *M. grandoculis.* r^2 values (model goodness of fit) are shown for each species. Biomass estimates are normalized (range of 0-1) to show patterns around the island rather than exact values and displayed on a square-root scale. Grid size is 300 m^2.

Environmental and human drivers of species occurrence: Case studies for M. grandoculis and A. lineatus using Boosted Regression Trees (BRT)

Here we present the results for species occurrence (presence/absence) distribution models using BRTs, focusing on *M. grandoculis* and *A. lineatus.* The final *M. grandoculis* model included fifteen predictors, with depth, seafloor rugosity, sediment, annual mean chlorophyll, calcifier cover,and population density showing the greatest importance, respectively (AUC_1 = 0.76; AUC_2 = 0.85; Figure 7a). Partial response curves for this model ensemble showed non-linear positive associations of depth, rugosity, sediment, and calcifier cover with species occurrence; chlorophyll and population density had negative relationships (Figure A1). Calcifier and sediment cover showed positive relationships with *M. grandoculis* occurrence, indicating that this species commonly occupies reef edge habitat. Annual mean chlorophyll had a negative relationship with *M. grandoculis* occurrence which may suggest a response to human-based pollution or runoff rather than ocean productivity. The final *A. lineatus* model included nine predictors, with depth followed by calcifier cover showing the greatest importance (AUC_1 = 0.93; AUC_2 = 0.96; Figure 7b). Depth had a negative relationship with occurrence while calcifier cover had a positive relationship. Longitude and rugosity likewise had positive associations with *A. lineatus* occurrence. For both species, depth played a substantially larger role in explaining occurrence than any other predictor.

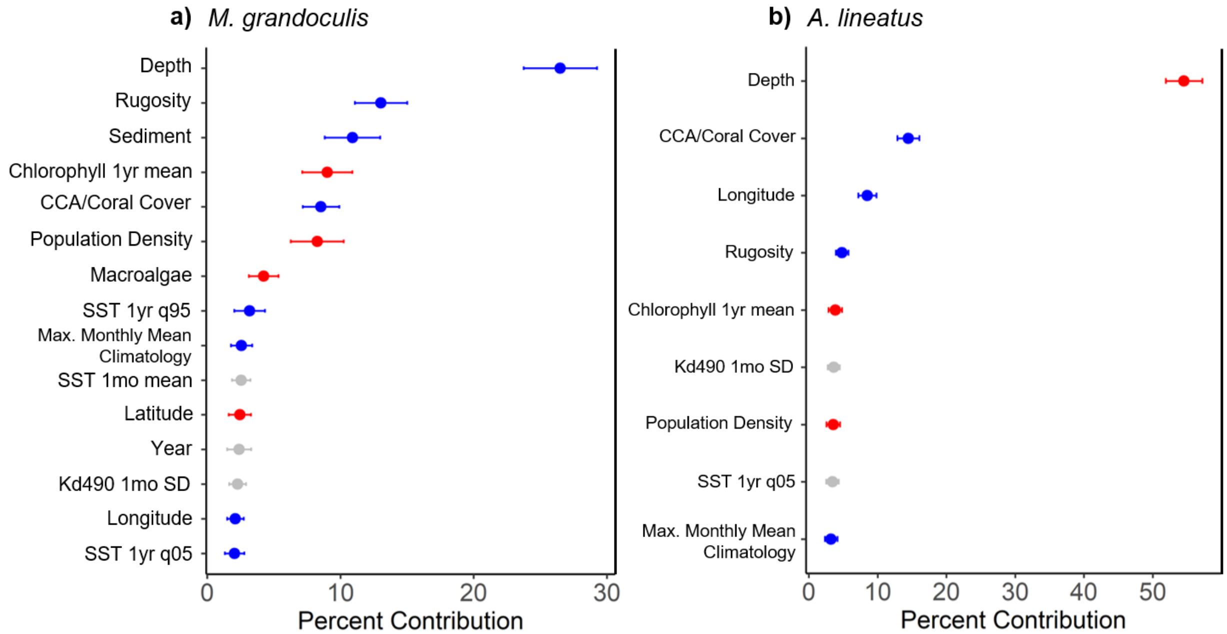

Figure 7. Mean percent contribution (± standard deviation) of environmental and human impact variables to the presence/absence (P/A) of (a) *M. grandoculis* and (b) *A. lineatus* determined by ensemble boosted regression tree models. Colors indicate the relationship between predictor variables and P/A responses, with blue indicating a positive relationship and red indicating a negative relationship. Gray indicates a relationship that is not clearly directional. The percent contribution of each predictor is a measure of its importance to the overall model fit. Note the different x-axis scales.BRT predictions for *M. grandoculis* occurrence suggest that this species is more likely to be present in deeper waters along the eastern and northern parts of the island (Figure 8a), as well as around the harbor. In exploring how changes to important predictor variables might shift the distribution of these species, we found that a 5% simulated increase in population density around Guam could lead to decreases of 2% in occurrence of *M. grandoculis* around the eastern sector, and harbor (Figure 8b). On the contrary, we found that a 5% decrease in population density around the island could potentially lead to increases of 2% in modeled occurrence in similar areas (Figure 8c). However, it is important to note that these kinds of effects would not happen overnight and could take years to manifest. BRT predictions for *A. lineatus* indicate that this species is more likely to occur along the western sector of the island in shallow waters, as well as along the eastern sector (Figure 8d). As calcifier cover was an important variable in this model, we explored the shifts that might occur with a 10% decrease to calcifier cover around the island and found decreases of *A. lineatus* modeled occurrence of more than 30% along southern, eastern, and northern coastline (Figure 8e). Conversely, we found that a 10% increase to calcifier cover around Guam could lead to increases of up to 30% in occurrence of *A. lineatus* in similar areas but further expanded to the south along the western coastline (Figure 8f).

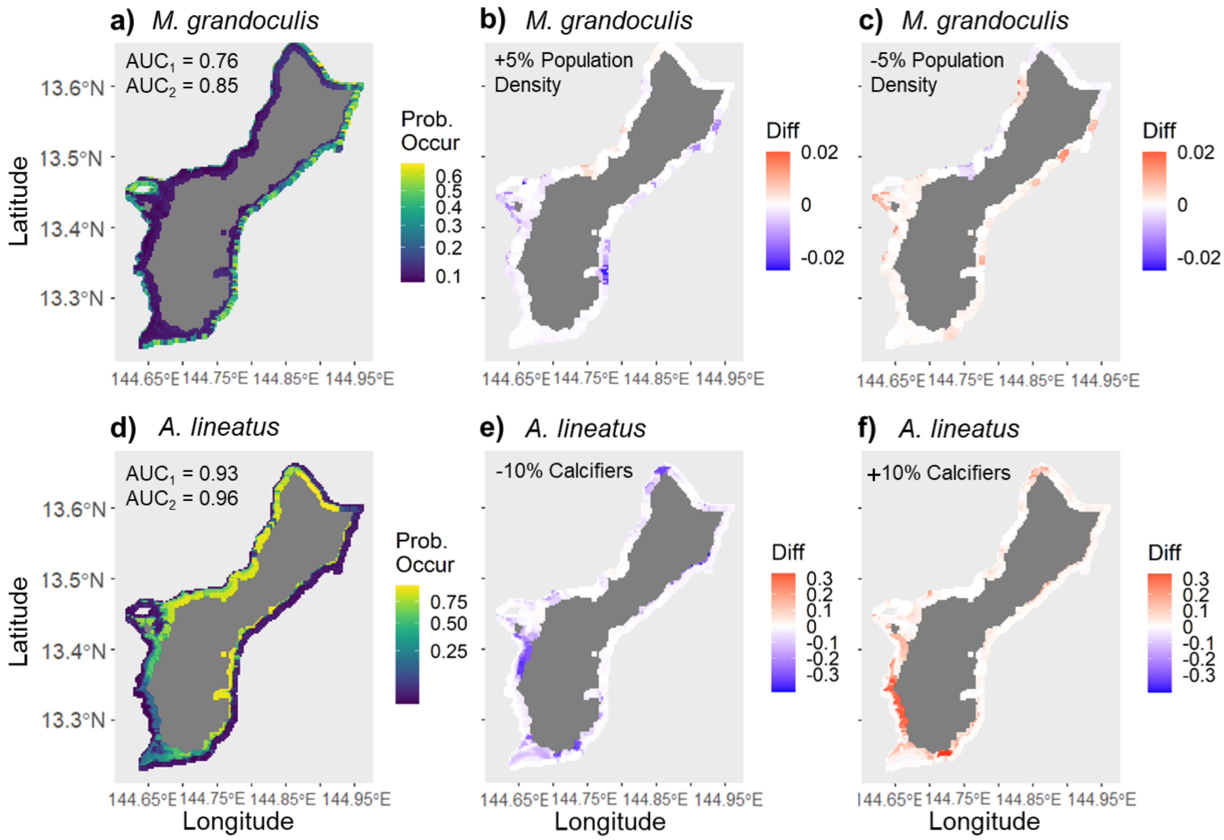

Figure 8. Maps of predicted probability of occurrence (Prob. Occur) from boosted regression tree models for (a-c) *M. grandoculis* and (d-f) *A. lineatus* between 0-30 m around Guam. (a) *M. grandoculis* predictions for the most recent NCRMP fish survey observations (10 Aug 2022), (b) change in predicted occurrence with a 5% increase in population density, and (c) change in predicted occurrence with a 5% decrease in population density. (d) *A. lineatus* predictions for the most recent NCRMP fish survey observations (10 Aug 2022), (e) change in predicted occurrence with a 10% decrease in calcifier cover, and (f) change in predicted occurrence with a 10% increase in calcifier cover. Grid size is 300m^2. AUC_1 reflects how well the model predicted new data (i.e., the 'test' sets). AUC_2 reflects how well the model predicted overall observations.

It is important to note the differences between the spatial GAMM prediction maps for *M. grandoculis* and *A. lineatus* (Figure 6a, e) and the BRT prediction maps for these same species (Figure 8a, d). The former prediction maps show modeled biomass estimates while the latter show modeled probability of occurrence estimates. The other major difference between these two results is that the spatial GAMMs focus almost entirely on the complex spatial patterns of distribution, while the BRT models focus on identifying the contributions of many different environmental and human factors. By the very nature of these models measuring different outcomes and different influencing factors, they lead to different conclusions.

Modeling with species groups

The final model for large parrotfish included nine predictors and revealed that annual mean chlorophyll-*a*, monthly mean SST, sediment cover, depth, rugosity, and calcifier cover had the strongest influences on this group's occurrence around Guam (Figure 9a). The model ensemble ultimately had poor predictive power but had decent explanatory skill (AUC_1 = 0.67; AUC_2 = 0.80). The positive importance of both sediment and calcifier cover is likely indicative of increased occurrence along reef edge habitats. This model also suggested a negative relationship between large parrotfish occurrence and population density as observed with *M. grandoculis*. The final model for small parrotfish was very different and included eleven predictors with calcifier cover followed by sediment clearly standing out as the most important variables (Figure 9b). The model ensemble had both decent predictive power and explanatory skill (AUC_1 = 0.76; AUC_2 = 0.88). Notably, it's important to mention that the data used for this model primarily reflects hard bottom surveys. For instance, locations like Piti Bomb Holes, with its extended seagrass and soft coral habitats near the shore, serve as major nursery habitats for small parrotfish. This information suggests that these habitats may play a significant role in the seeding system for this species. Population density was only marginally important in this model and had a slightly positive relationship with small parrotfish occurrence.

When the model results were predicted around the entire island between 0 and 30 m, predicted large parrotfish occurrence was considerably more variable than small parrotfish. This group showed the greatest predicted occurrence around Pati Point and the eastern coastline broadly, but minimal occurrence along the western coastline (Figure 9c). Conversely, small parrotfish showed consistently high predicted occurrence nearly all around the island, particularly at deeper depths (Figure 9d). Overall, the predicted occurrence for the small parrotfish group was much higher than that of the large parrotfish group.

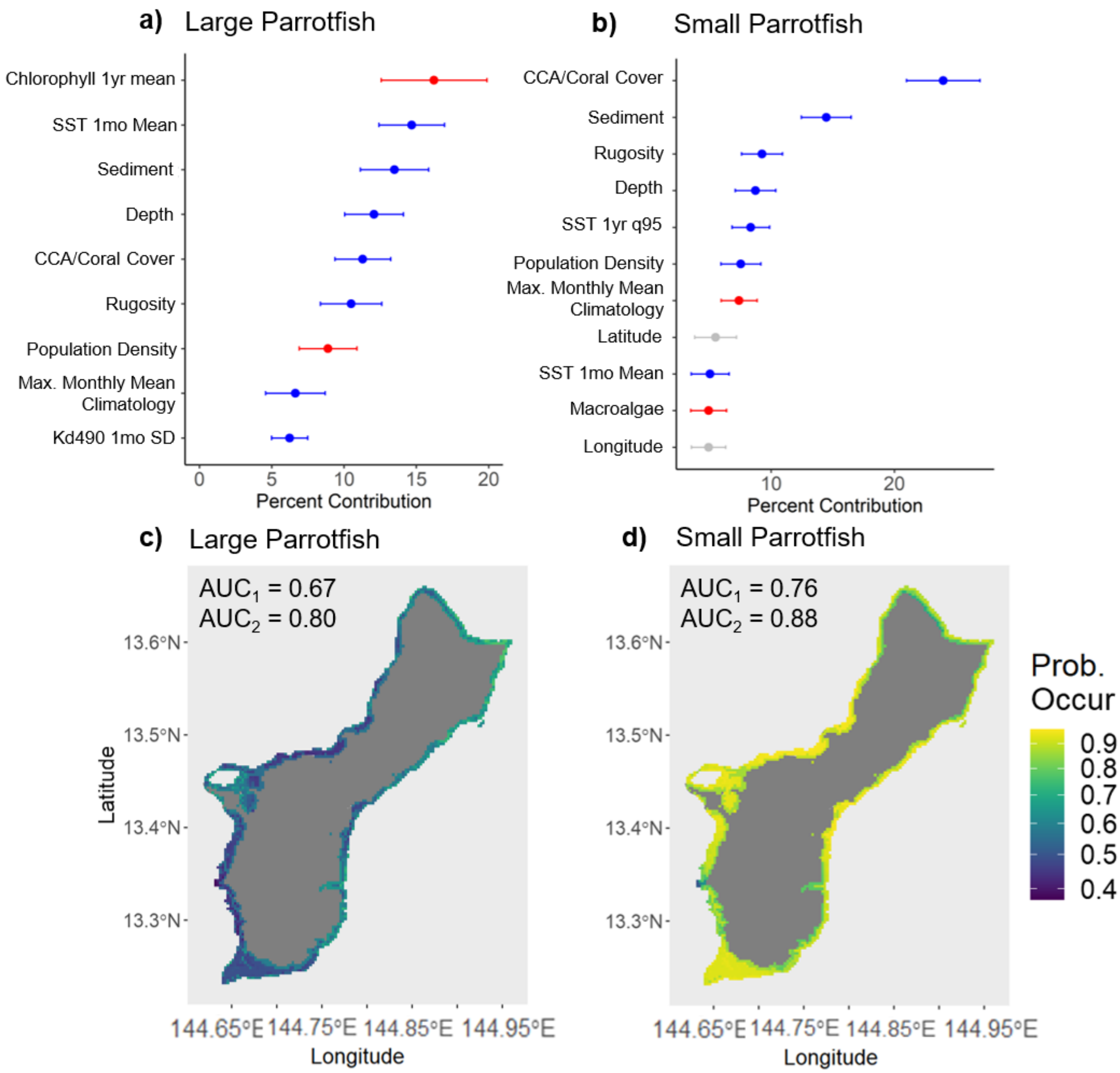

Figure 9. (a,b) Percent contribution of environmental and human impact variables to the presence/absence (P/A) of (a) large parrotfish (> 50 cm) and (b) small parrotfish (< 50 cm) determined by ensemble boosted regression tree models. Colors indicate the relationship between predictor variables and P/A responses, with blue indicating a positive relationship and red indicating a negative relationship. Gray indicates a relationship that is not clearly directional. The percent contribution of each predictor is a measure of its importance to the overall model fit. Note the different x-axis scales. (c,d) Maps of predicted probability of occurrence (Prob. Occur) from boosted regression tree models for (c) large parrotfish and d) small parrotfish in waters 0-30 m depth around Guam for the most recent NCRMP fish survey observations (10 Aug 2022). Grid size is 300m^2. AUC1 reflects how well the model predicted new data (i.e., the 'test' sets). AUC2 reflects how well the model predicted over all observations.

Discussion

Applying advanced spatial modeling techniques to five years of fish survey data from Guam's nearshore habitats enabled us to generate species distribution models and prediction maps for five priority reef fish species. Of these, *M. grandoculis* had the most reliable model-based biomass estimates with respect to observations ($r^2 = 0.87$; Figure 6e), though predicted biomass was typically lower than observations at the island sector level for this species (Figure 4e). While *A. lineatus* had model-based biomass estimates that were slightly less reliable overall ($r^2 = 0.51$; Figure 6a), predicted biomass for this species agreed well with observations at the island sector level (Figure 4a). The reliability of these model-based estimates varies across spatial scales (i.e., island vs. sub-island). This variability should be considered when interpreting species-specific biomass results for management at these different scales.

The model-based biomass estimates suggested that three species (*A. lineatus, S. schlegeli,* and *M. grandoculis*) showed clear trends with depth, while two others *(N. literatus, C. melampygus*) did not strongly associate with any particular depth bin within the 0 to 30 m survey domain. The lack of depth trends may be real but could also be a sampling artifact, as our survey design did not capture the full depth ranges of all species.

Guam's five major marine preserves were established in 1997 and enhanced in 2006 with additional restrictions to development, construction, drilling, and trenching ("Guam's Marine Preserves"). While some of the preserves do allow fishing activities such as shore-based hook and line fishing within the Pati Point preserve and allowances for certain juvenile reef species and fishing along the reef margin in Tumon Bay, these areas do show evidence of enhanced fish biomass relative to other island areas. Tumon Bay and Pati Point appear to have consistently higher biomass for several of the species we were able to model relative to the other preserves and island sectors (Figure 4). *A. lineatus, N. literatus,* and *M. grandoculis* show considerably increased biomass within Tumon Bay, and these species along with *C. melampygus* show considerably increased biomass within the Pati Point marine preserve. On the contrary, *S. schlegeli* appears to have the highest biomass within the Piti Bomb Holes preserve and the harbor. *C. melampygus* biomass remains fairly low across the island; the only hotspot is within Pati Point. Overall, the marine preserves appear to be favorable for enhanced priority species' biomass, though to variable degrees.

Understanding the geographical context of an area is crucial when interpreting model-based findings. Guam's eastern and western reef systems exhibit significant differences. Eastern systems generally have less developed reef flats and steeper reef slopes, representing a smaller area and less strata of the same type compared to the western reefs. This means that, from a biomass perspective, in an unfished condition, the western reefs would naturally contribute significantly more to the total biomass due to their greater habitat extent. Militarized areas and privately owned land around Guam likely also play a role in preserving reef fish biomass, as these areas limit access to fishing similarly to MPAs. For example, the Anderson Air Force Base occupies most of the island's northern coastline (and includes Pati Point marine preserve), and biomass estimates for this area were relatively high for several species (Figure 6). Further, much of the island's eastern coastline is blocked from public use by private land ownership (J. Brown, pers. comm) and is difficult to access from shore due to rougher sea states and being greater distance from boat ramps, likely resulting in the relatively high biomass estimates for species like *A. literatus, N. lineatus,* and *M. grandoculis*.

While habitat depth and protected areas play a large role in reef fish distributions around Guam, numerous environmental and human influence variables also affect fish biomass at island and sub-island scales and at various temporal scales. Using a machine learning model-based approach (BRT) to explore these environmental drivers revealed unique scenarios for two case study species, *M. grandoculis* and *A. lineatus*. *M. grandoculis* is a commonly speared or hook-and-line caught species that generally inhabits sandy peripheries or rubble areas around coral reefs, roughly within the depth range of 5 to 30 m (Carpenter & Allen, 1989) but has been observed down to depths around 100 m (Pyle et al., 2016). *A lineatus* is typically speared or caught with large nets and inhabits rock and coral substrates at reef edges between 0 to 10 m, though usually less than 3 m (Mundy, 2005 and references therein). The results of our models for both species align well with these habitat associations. Calcifier cover and sediment were both important variables for *M. grandoculis* occurrence, which together are indicative of reef edge habitat adjacent to sediment. Depth and calcifier cover were both important for *A. lineatus* occurrence.; together they indicate that shallow habitat within areas of high reef cover are crucial for the species.

In addition to depth, which had nearly opposite relationships with occurrence for these two species, human population density, seafloor rugosity, and calcifier cover were also top predictors in the models. The ecological importance of these variables is characterized by their significant contributions to model performance, as they were used most often for tree splitting in the model's decision-making process. The distinct relationships between these drivers and species occurrence are consequential, particularly considering the observed trends in coral cover (and rugosity) and population density over time. Coral cover has declined significantly around Guam in recent years due to successive bleaching events that began in 2013 (Raymundo et al., 2019), and will likely continue to decline as ocean temperatures continue to increase throughout the region (Figure 3). As human population continues to increase steadily on the island, fishing pressure, pollution, and runoff also increase. Our model predictions provide a valuable tool to identify where changes to species occurrence could be most substantial under changing human impact and environmental conditions. However, these predictions also highlight the areas where efforts toward reduced fishing pressure and reef restoration could most strongly benefit the occurrence of reef fish species. In these scenarios, it is important to recognize that the model-predicted changes in species occurrence with restorative efforts would not happen overnight—rebuilding fish stocks takes time. Rather, these results highlight the positive effects that restorative efforts could have on reef fish species in the long term.

Shifts in environmental conditions are reshaping the interactions between reef fish species and their habitats in Guam and the CNMI. These changes, such as an increase in SST, shift in primary productivity, and prolonged anthropogenic stressors, carry ecological implications for local communities that depend on these living marine resources. Decadal increase in SST can alter the distribution and behavior of reef fish species, potentially influencing the availability of these species to local fishers, subsequently impacting the local economy. Changes in primary productivity could disrupt the local food web structure, which could have broader consequences on the reef fish populations. Anthropogenic stressors like overfishing and habitat degradation can further compound these effects, highlighting the intricate interplay between natural and human-induced changes. By investigating the links between species distributions and changing environmental factors, this research enhances our understanding of how reef fish biomass and distribution respond to various top down and bottom up pressures, providing valuable insights for effective fisheries management and the conservation of marine resources in Guam and the CNMI.

In addition to individual species distribution evaluations, we provide examples of how species can be grouped together in a meaningful way and their occurrence evaluated as a complex (Figure 9). This approach could help overcome the limitations of rare or sparsely observed species that could not be modeled individually. Through this approach, we found significant differences between the important human and environmental drivers of large and small parrotfish occurrences around the southern Mariana Islands, as well as strong differences in the distributions of these groups around Guam. Further, large parrotfish occurrences were negatively influenced by human population density but small parrotfish were not, which suggests that fishing pressure and coastal access influence the size and occurrence of this species complex. This was expected since large-bodied parrotfish typically experience much higher fishing pressure (Lindfield et al., 2014), which is why many of these species were individually sparse in the NCRMP fish surveys.

We presented BRT outcomes and predictions for two priority reef fish case studies, *M. grandoculis* and *A. lineatus*, as well as two grouped species complexes (large and small parrotfish). These serve merely as examples of the substantial insight that can be gained from this methodology. Generating such models for an entire suite of reef fish species would provide a robust investigation into both environmental and human influences on reef fish biomass across the Mariana Islands and perhaps the entire U.S. Pacific Islands Region.

Management Implications

The overarching goal of this work was to provide a suite of scientific tools that can be used to explore and quantify spatiotemporal trends in target reef fish distributions, identify potential top-down and bottom-up variables that can be used to predict changes in those distributions, and offer potential logistical pathways to various approaches for addressing jurisdiction-specific, management-relevant questions.

Our study demonstrated how existing satellite data sets can be used to establish baseline conditions and detect shifts in the local environmental conditions of reef fisheries and associated habitats around Guam. Additionally, we illustrated that existing fishery-independent monitoring efforts by NOAA NCRMP can be used to: (1) quantify the magnitude of environmental and anthropogenic drivers affecting the biomass distributions of target species biomass, and (2) provide robust statistical inferences to support spatial management of target species beyond field observations. Our results showed the critical importance of considering spatial scales when utilizing statistically derived biomass estimates for decision-making within JCR-FMP, such as identifying potential detrimental habitat drivers and developing plans to protect specific portions of target species biomass during particular life stages (e.g., spawning stock biomass). It's worth noting that the reliability of such estimates may vary at different temporal and spatial scales, as well as among different species.

Within the NOAA NMFS Essential Fish Habitat framework (Laman et al., 2018), this research offers a suite of scientific tools designed to address the first two levels of management-relevant EFH information, which includes assessing presence-absence and conditional density. Using these scientific tools, we demonstrated that further appropriately designed statistically randomized monitoring efforts, with a particular focus on specific life stages of the target species, can bring us closer to identifying effective management options (e.g., identifying temporally stable core habitats defined as the top 25% cumulative percentiles of the spatially varying biomass distribution of known spawning size classes). These options may include protecting specific segments of a target species' reproductive population at management-relevant spatial scales, thereby offering essential logistical guidance for managers to establish more precise and specific targets. Furthermore, our work indicates that the distributions of priority reef fish species are likely to undergo changes as habitat conditions change. Future research should build upon our assessments of human and environmental drivers of species distributions by incorporating additional priority reef fish species across various management-relevant scales.

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Appendix

a) *M. grandoculis*

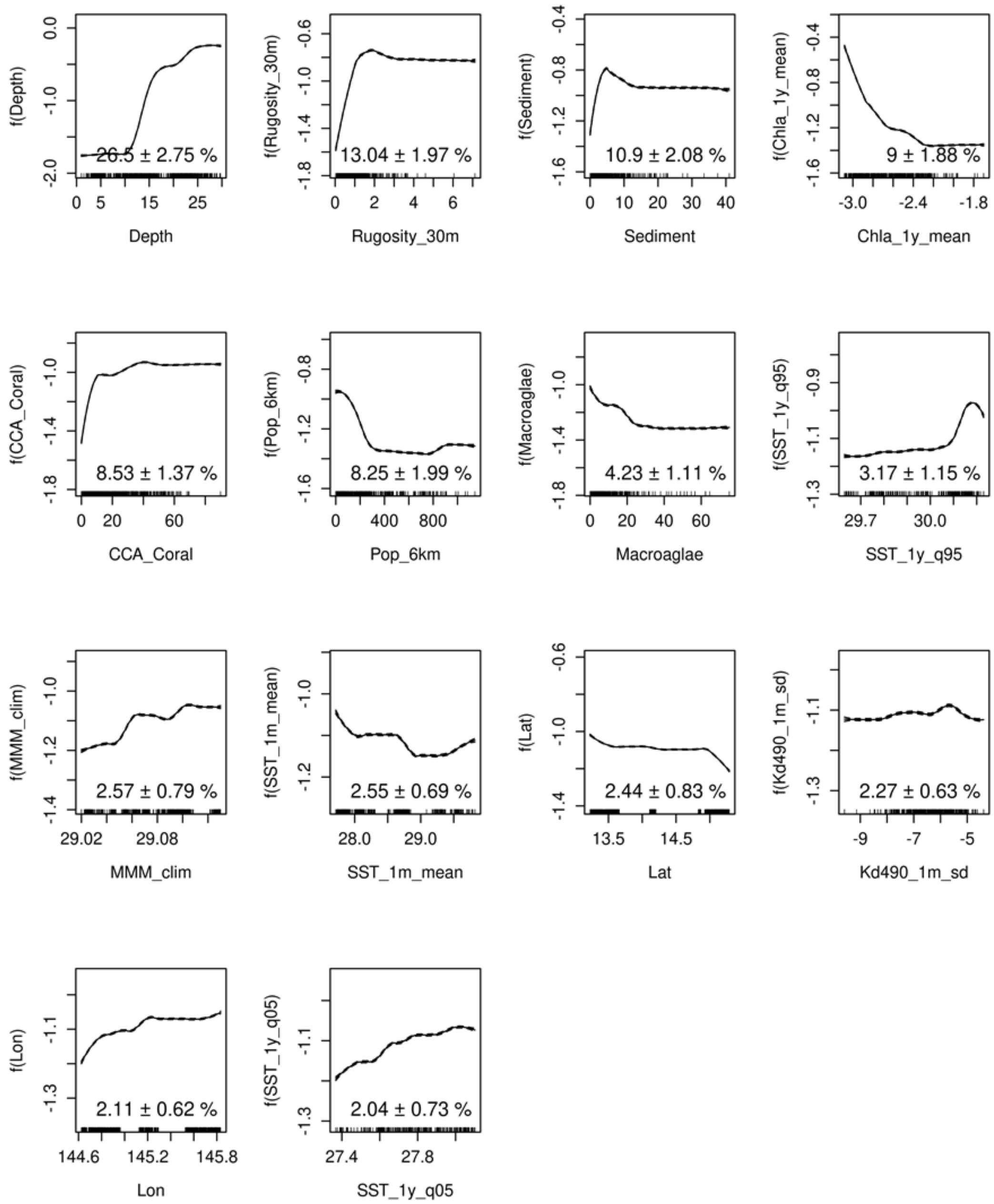

Figure A-1. Partial response curves for *M. grandoculis* optimal probability of occurrence Boosted Regression Tree models. Panels show percent contribution (± st.dev) of each predictor variable and each curve shows the smoothed averages of each predictor variable and each curve shows the smoothed averages of each 100-model ensemble.

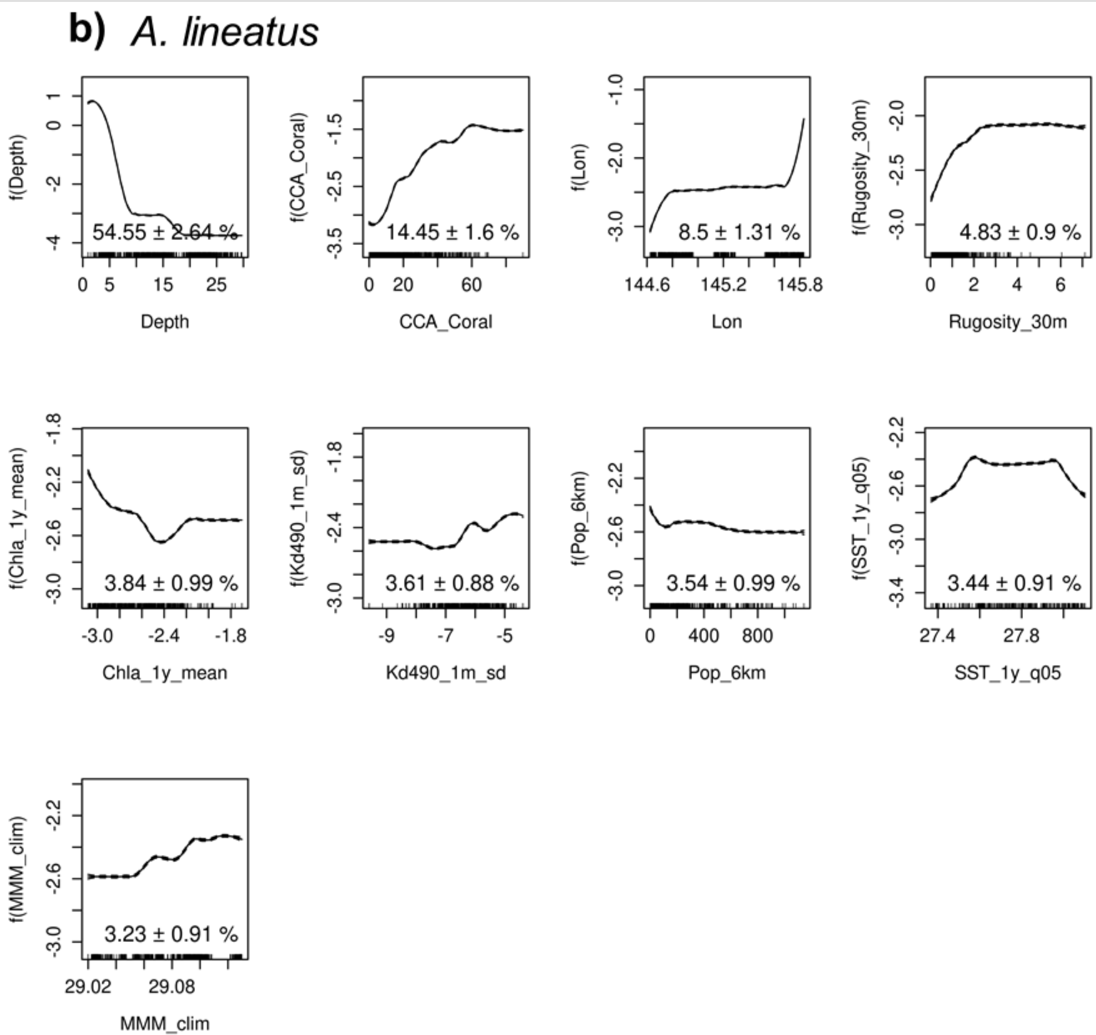

Figure A-2. Partial response curves for *A. lineatus* optimal probability of occurrence Boosted Regression Tree models. Panels show percent contribution (± st.dev) of each predictor variable and each curve shows the smoothed averages of each predictor variable and each curve shows the smoothed averages of each 100-model ensemble.

Table A-1. List of scarid species (parrotfishes) observed in the NCRMP fish surveys and used for the grouped species analysis. Maximum observed sizes (TL) were obtained from FishBase.

Species	Max. size (cm)	Group
Calotomus carolinus	54	Large
Calotomus zonarchus	23	Small
Chlorurus bicolor	50	Large
Chlorurus ocellatus	80	Large
Chlorurus frontalis	50	Large
Chlorurus japanensis	56	Large
Chlorurus microrhinos	58	Large
Chlorurus perspicillatus	61	Large
Chlorurus spilurus	27	Small
Hipposcarus longiceps	56	Large
Scarus altipinnus	53	Large
Scarus chameleon	31	Small
Scarus dimidiatus	26	Small
Scarus dubius	26	Small
Scarus festivus	45	Small
Scarus forsteni	55	Large
Scarus frenatus	42	Small
Scarus fuscocaudilus	25	Small
Scarus ghobban	59	Large

Species	**Max. size (cm)**	**Group**
Scarus globiceps	34	Small
Scarus niger	32	Small
Scarus oviceps	27	Small
Scarus psittacus	36	Small
Scarus rubroviolaceus	63	Large
Scarus schlegeli	30	Small
Scarus spinus	30	Small
Scarus tricolor	53	Large
Scarus xanthopleura	54	Large