Impacts of pollution, fishing pressure, and reef rugosity on resource fish biomass in West Hawaii

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Abstract. Human activities and land-use drivers combine in complex ways to affect coral reef health and, in turn, the diversity and abundance of reef fauna. Here we examine the impacts of different marine protected area (MPA) types, and various human and habitat drivers, on resource fish functional groups (i.e., total fish, herbivore, grazer, scraper, and browser biomass) along the 180 km west coast of Hawaii Island. Across survey years from 2008 to 2018, we observed an overall decrease in total fish biomass of 45%, with similar decreases in biomass seen across most fish functional groups. MPAs that prohibited a combination of lay nets, aquarium collection, and spear fishing were most effective in maintaining and/or increasing fish biomass across all functional groups. We also found that pollution, fishing, and habitat drivers all contributed to changes in total fish biomass, where the most negative impact was nitrogen input from land-based sewage disposal. Fish biomass relationships with our study drivers depended on fish functional grouping. For surgeonfish (grazers), changes in biomass linked most strongly to changes in reef rugosity. For parrotfish (scrapers), biomass was better explained by changes in commercial catch where current commercial fishing levels are negatively affecting scraper populations. Our observations suggest that regional management of multiple factors, including habitat, pollution, and fisheries, will benefit resource fish biomass off Hawaii Island.

Key words: fish biomass; functional group; habitat complexity; herbivore; local disturbance; marine protected area.

INTRODUCTION

Coral reefs represent one of the most diverse ecosystems in the world, providing invaluable services such as protecting coastlines from erosion and supporting more than 25% of marine species (Moberg and Folke 1999, Burke et al. 2012, Grafeld et al. 2017). Coral reefs and associated fauna are experiencing increased pressure from global stressors, including bleaching events that are projected to occur with greater frequency (van Hooidonk et al. 2016, Hughes et al. 2017). These events occur against a background of variability among local human and habitat influences. Factors such as fishing pressure, reef rugosity, and nitrogen input can all have substantial impacts on coral reef fish assemblages (Friedlander et al. 2017). Understanding the relative influence of these drivers is important in assessing pathways for managing and protecting coral reef systems and reducing secondary stressors during repeated marine heatwaves that cause coral bleaching.

Fish biomass can be used as an indicator of reef status and human disturbance, particularly through fishing impact (McClanahan et al. 2016). Reef fish are a major source of protein that feeds over one billion people worldwide (Duffy et al. 2015). Resource species, targeted fishes ultimately intended for human consumption, are a critically important component in coral reef ecosystems as they consist predominantly of herbivorous species (Division of Aquatic Resources 2018). The role of herbivorous fish in coral reef ecosystems is particularly important in balancing coral-algal dynamics (Heenan and Williams 2013, Smith et al. 2016). Herbivorous fish, such as parrotfishes that scrape algae from coral reef surfaces, are key in promoting reef calcifiers (e.g., Scleractinians and crustose calcifying algae) over fleshy macroalgae (Mumby et al. 2006, Hughes et al. 2007, Topor et al. 2019). This, in turn, is important for reef recovery after bleaching events (Graham et al. 2015). In response to over-harvesting of grazers, coral reefs are highly likely to transition to that of algal dominance in

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Article e02213; page 1
areas more impacted by humans (McClanahan et al. 2007, Jessen et al. 2013, Graham et al. 2015).

The physical structure of reefs greatly influences biodiversity and ecosystem functioning. Topographically complex reefs generally support diverse communities (González-Rivero et al. 2017), while disturbances such as climate change, including increased tropical cyclones, can generate decreases in reef rugosity, a metric of reef topography (Smithers et al. 2007). Increasing reef rugosity increases the availability of refuge spaces such as crevices and branches, which in turn can help to increase fish biodiversity (Alvarez-Filip et al. 2011, González-Rivero et al. 2017). An increase in total fish diversity, abundance and biomass is generally observed in more structurally complex and diverse reef habitats (e.g., Gratwicke and Speight 2005, Idjadi and Edmunds 2006, Wilson et al. 2007).

There are substantial differences in reef habitat in the Hawaiian Islands, as well as potentially different influences of human drivers. The bulk of commercial, recreational, and subsistence catch of resource fish, as well as invertebrates and seaweed, are from the near-shore reef habitat (McCoy et al. 2018), where the majority of herbivore biomass is observed at a shallow depth range of 4.3–7.2 m (Friedlander and Parrish 1998). In addition to these factors, nitrogen pollution is prevalent along many parts of the coastline owing to human wastewater that is primarily disposed via onsite sewage disposal systems (OSDS) (Wedding et al. 2018). Additionally, other land-use types such as golf courses increase nutrient runoff and leaching of other pollutants into the nearby reef (for a review, see Carlson et al. 2019). Thus, the influence of local drivers is key in shaping fish biomass in Hawaii, with near-shore ecosystems being particularly vulnerable due to their proximity to land. Changes in reef fish biomass can often be more sensitive to local human impacts than changes in benthic diversity and cover on coral reefs (McClanahan et al. 2011). Furthermore, local impacts can intensify the effect of marine heat waves or climate change impacts (Bruno and Valdivia 2016). Nonetheless, mitigation of local stressors can help to compensate for climate change impacts (Brown et al. 2013). An understanding of which human impacts most strongly drive changes in fish biomass will therefore be important in driving adaptive policies in local management.

Here we use shallow water resource fish (SWRF) survey data from 2008–2018 collected along the west coast of Hawaii Island (henceforth “West Hawaii”) to investigate three main objectives: (1) observe changes in resource fish biomass over survey years, (2) determine the influence of various marine management strategies on fish biomass, and (3) assess the relative importance of pollution, fishing and environmental drivers on fish biomass. We hypothesize that resource fish biomass has decreased over time; however, this decline is likely to be functional group specific. We also hypothesize that no-take reserves will contain the greatest fish biomass, as seen for other no-take areas globally (Sala and Giakoumi 2018). Last, we hypothesize that fishing pressure would most strongly impact standing biomass of resource fishes in comparison to other human and environmental impacts. Understanding drivers behind patterns of functionally important groups of fishes is crucial to understanding where management can be most effective in reducing stressors on coral reef ecosystems.

METHODS

Study region

West Hawaii supports a biologically diverse reef ecosystem, housing a contiguous reef of almost 180 km; the largest in the main Hawaiian Islands. The resident population has increased threefold since 1970, where ~45% of Hawaii’s population live in West Hawaii; 25% within 1 mile (1 mile = 1.6 km) from the coast (Gove et al. 2019). Reefs in West Hawaii support ecosystem services of tremendous value to local communities. Local stressors such as nutrient runoff, fishing pressure, and coastal development are increasingly impacting near-shore ecosystems, with similar pressures across the entire Hawaiian archipelago. An understanding of the responses of these systems and associated fauna is critically important, where West Hawaii provides a model system for efforts elsewhere in the Main Hawaiian Islands and beyond.

Surveys

We analyzed fish data collected in 2008, 2009, 2011, 2014 and 2018 as part of Hawaii’s Department of Land and Natural Resources’ Division of Aquatic Resources (DAR) monitoring program of shallow water resource fish, at a total of 349 sites across all survey years (Fig. 1). Resource species are recognized as species
FIG. 1. Shallow water resource fish survey locations for all survey years and marine managed areas in West Hawaii. The left panel shows the survey locations separately for each survey year, where sites were determined by using ArcGIS to generate and evenly distribute sites along the shallow nearshore habitat of West Hawaii. Sites are color coded to match the marine managed area the survey fell within. The right panel shows the marine managed areas in West Hawaii colored by the management types covered by the surveys, where blue and gray marine managed areas are both considered open.
important to local subsistence or cultural sectors (Appendix S1: Table S1; Friedlander et al. 2017), providing substantial benefits for the economy, cultural practices, and food security in Hawaii (Grafeld et al. 2017). Each round of surveys consisted of 68 to 72 sites each survey year that were predetermined by using ArcGIS v 9.2 to generate and evenly distribute survey sites along the West Hawaii coastline between the northern and southernmost ends. Sites were selected within the 2–6 m isobath range within hard-bottom habitat where, generally, each site was surveyed once. Surveys were typically completed across a 2–3 month period, where survey timing varied across years (April to October 2008, February to April 2009, August to September 2011, October to December 2014, February to April 2018). Visual surveys were used to quantify the abundance of resource fish species (e.g., the whitebar surgeonfish Acanthurus leucopareius and the bullethead parrotfish Chlorurus spilurus) in shallow water habitats during a timed swim (10 minutes). During the surveys, divers remained with the 2–6 m depth range over hard-bottom habitat.

Survey methods of resource fish

The dive survey team consisted of two divers with both divers surveying the same 5 m wide belt, with an assumed central line projected forward along the reef isobath between the two divers. A 10-minute timed swim was used to survey fish (Caldwell et al. 2016) where one diver towed a handheld Garmin GPS (Garmin International, Inc., Olathe, Kansas, USA) and marked the start and end waypoints. ArcGIS was used to determine the area of the survey based on the recorded survey track. The average distance from start to end waypoints across all surveys was 232 m. Throughout the duration of the survey, divers remained within the 2–6 m depth range by following the reef contours. The leading diver was responsible for counting and sizing parrotfishes, wrasses, and other resource fish that were larger than 15 cm total length. The second diver was responsible for counting and sizing surgeonfishes, goatfishes, and introduced species larger than 15 cm in total length. Additionally, convict tang Acanthurus triostegus, Achilles tang Acanthurus achilles, and goldrim tang Acanthurus nigricans were surveyed when larger than 10 cm in total length due to a smaller average size but importance as resource fishes.

The main response variable considered in this study was the estimated biomass of fishes per unit area (g/m²). The mass of individual fishes was estimated using length to weight conversion parameters from FishBase, a web-based resource (Froese and Pauly 2010). Data were pooled into total fish biomass and into four other fish functional groups. These included herbivores as a single guild that was further subdivided into three functional groupings: scrapers, grazers, and browsers, based on diet information taken from Heenan et al. (2016; Appendix S1: Table S1). Understanding the impacts across different functional groups of fish is important because their individual roles on reefs differ and considering them by their feeding mode can help to quantify herbivory as an indicator of resilience (Heenan and Williams 2013). Additionally, understanding impacts of local drivers on specific functional groups will be important for local management to better adapt policies that protect groups of fish with differing compositions. In this data set, scrapers primarily consisted of parrotfish species such as the palenose parrotfish Scarus psittacus, which feed on epilithic algal turf, and some Chlorurus species, which remove some component of the reef as they feed, contributing to bioerosion. The grazers from these surveys were all species of surgeonfishes from the genus Acanthurus such as the whitespotted surgeonfish A. guttatus. They feed on a combination of epilithic algal turf and sediment. In this data set, the browsers consisted of certain unicornfishes and parrotfishes such as bluespine unicornfish Naso unicornis and stareye parrotfish Calotomus carolinus that primarily feed on macroalgae, removing only algae from the substrate (Green and Bellwood 2009).

Change in resource fish biomass across survey years

To assess change in resource fish biomass across each year, we used bootstrapping with 10,000 iterations to generate 95% confidence intervals (CI) of mean fish biomass for each survey year and functional group. Non-overlapping 95% CIs is an indication that biomass is significantly different between years (Smith 1997, Cumming and Finch 2005).

Effects of protection type on resource fish biomass

For each site, the MPA status was determined (Hawaii State GIS, geodata.hawaii.gov). As SWRF sites were randomly selected with up to 72 sites each survey year, different MPA types were unequally represented, particularly for full no-take areas given that they make up only a very small combined area (~0.6 per km²) in West Hawai‘i. Across all survey years, the number of sites that were open, i.e., had no protection (n = 144) or only banned aquarium fishing (n = 102) heavily outnumbered the other protection type sites, and therefore there was a lack of statistical power to consider this full analysis. We present total fish biomass across all MPA and open areas in Appendix S1: Fig. S1 for visual comparison only.

For our analysis, we focused on management types that banned different gear types: full no-take areas (n = 5), areas that banned lay nets (n = 39), areas that banned lay nets and aquarium fishing (n = 46), and areas that banned lay nets, aquarium, and spear fishing (n = 13). When a site represented multiple MPA categories, it was categorized as the MPA with the stricter regulations so that each site only represented one category.
Our objective was to determine the effect of protection type on resource fish biomass; however, this can be affected by the age of an MPA, especially since some of the no-take areas were only established in 2016. Thus, an analysis of covariance (ANCOVA) was used to determine whether there were statistical differences among the mean biomass across different MPA types, with MPA age as a covariate. We used the anova function in R to build a model with MPA type as a fixed factor and MPA age as a covariate. We performed five different ANCOVAs for the various functional groups (total fish, herbivores, scrapers, browsers, and grazers). To meet the assumptions of ANCOVA, the cube root across all functional group biomass values were taken. These transformations ensured that data were both normal and homogenous. Tukey’s post hoc tests were used to determine which MPA types significantly differed from each other. Untransformed data are presented in Fig. 2 to assist interpretation.

Local drivers of fish biomass

Reef complexity and nutrient levels represent some of the factors that most strongly predict a resilient reef (Graham et al. 2015) and is why these factors were included in our models. We analyzed co-located data on a range of human and habitat variables known to impact reef fish with the SWRF survey data across all years (Table 1). Year was not considered in the final model as the appropriate driver data for the year prior to each survey year was used in the analyses as conducted in multiple studies (Williams et al. 2015, Heenan et al. 2016, Friedlander et al. 2017).

Fishing drivers

Fishing driver data included both commercial and non-commercial catch (Table 1). Data for commercial catch included the total commercial catch in kilograms per hectare of reef fish species calculated for the year prior to each survey year. Non-commercial yield of reef fish was also estimated for the year prior to each survey year in kilograms per hectare. Accessibility was embedded as a layer within the non-commercial catch data (McCoy et al. 2018, Wedding et al. 2018), based on steepness of terrain within 100 m of the shoreline and distance to nearest boat launch. The 2013 data were used for the 2018 surveys because estimates of non-commercial catch for years after 2013 do not exist (Wedding et al. 2018). See Table 1 for full explanations of human drivers, estimations of catch, and spatial resolution.

Pollution drivers

Land-use driver data included nitrogen pollution from golf courses and nitrogen pollution from OSDS such as cesspools, septic tanks, and injection wells, calculated for the year prior to each survey year (Table 1). Nitrogen pollution from golf courses was calculated in kilograms per hectare, proportional to the area of golf course within subwatersheds upslope of each survey site, with an offshore dispersion model. Nitrogen pollution from OSDS (kg/ha) was limited to OSDS located within a modeled 1-yr travel time of ground water to the coast from inland. This represents a conservative estimate as OSDS located further inland than the 1-yr travel time are not included the final value. See Table 1 for explanations of nitrogen flux estimation and spatial resolution.

Habitat driver

A habitat driver variable of reef rugosity was included in our analysis. Bathymetry and benthic rugosity mapping data were collected in 2018 using the Global Airborne Observatory (GAO; formerly the Carnegie Airborne Observatory; Asner et al. 2012). The method is described in Asner et al. 2020, which utilizes airborne high-fidelity imaging spectroscopy to derive bathymetry to 25 m depth at 1 m spatial resolution. Their reported precision was 0.5 m and absolute uncertainty of approximately 1.2 m (Asner et al. 2020). We determined reef rugosity for each transect by using the start and end GPS coordinates recorded for each survey with a 5 m width to represent the area that was covered during the surveys. Using the bathymetric maps, surface area to planar area rugosity was calculated for each transect by dividing the total contoured surface area by the total planar area, where more complex surfaces have a higher value than smooth surfaces. A caveat in our study is that we assumed that the underlying benthic 3D complexity remained similar between survey years despite a bleaching event in 2015. Despite coral mortality from that event, most dead branching and massive coral skeletons remained and continued to provide structure (particularly at the 1 m resolution of the rugosity data), where reef rugosity takes a longer time to degrade (Bozec et al. 2014, Perry and Morgan 2017). This means that, in the data analysis, the rugosity values for each site were all derived from GAO imaging spectroscopy data that was collected between June 2017 and January 2018 (Asner et al. 2020), with the assumption that sites surveyed prior to 2017 would not have changed in rugosity in the interim.

Modeling driver importance

As our objective was to assess the relative importance of pollution, fishing, and environmental drivers on fish biomass, we used multimodel inference paired with generalized additive modeling to quantify the importance of each driver. This methodology has been utilized previously to weight variables of importance and explore nonlinear relationships (Bekkby et al. 2009, Heenan et al. 2016, Fisher et al. 2018, Ravindra et al. 2019). All statistical procedures were performed in R software (v 3.1.2). Collinearity among predictor variables was assessed prior to all analyses using variance inflation...
factors (VIF) where the highest VIF for any predictor was 2, lower than our a priori cut-off value of 3 (Zuur 2012). All variables were able to be retained in the models due to low collinearity. Furthermore, we used Moran’s I to test for spatial autocorrelation. For all variables, the values were close to 0 and therefore a lack of autocorrelation existed among our variables.

Considering each site across each year as individual data entries, we used generalized additive models (GAM) to model the relationships between various groupings of resource fish biomass and various predictor variables using the mgcv package in R (Wood 2012). Models were fitted with a negative binomial distribution, which suited our over-dispersed count data of fish. Overfitting can be a problem with GAMs (Wood 2008) thus we limited the number of knots to five to prevent overfitting of our models.

We used model selection and averaging procedures from the MuMIn R package (Barton 2013) calculating Akaike’s Information Criterion (AIC) corrected for small sample size (AICc; Anderson 2008) and the AICc-based relative importance weights ($w_i$) where, for each response variable, all possible models with the predictor data set were run using the dredge procedure. We retained only models with Akaike weight $>0.05$ where the variable importance output (Table 2) gives the total weight of each variable for all models. As models sum to 1, values close to 1 indicate predictor variables that occur in large portions of the models. With the retained models, we generated a weighted model average that we then used for model prediction.

Relationships between response and predictor variables were generated using the predict procedure, which generates visualizations of smoothers of the top-ranked...
Table 1. Predictor variables used in this study.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Label</th>
<th>Spatial resolution</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commercial Fishing Yield of Reef Fish</td>
<td>Commercial catch</td>
<td>Reporting blocks (Appendix S1: Fig. S2)</td>
<td>Total commercial catch (kg/ha) of reef fish species per hectare, by reporting block clipped to 40 m depth contour, excluding MPAs by gear type, reported by commercial marine fishing license holders including commercial line, net, and spear fishing annual catch</td>
</tr>
<tr>
<td>Non-Commercial Fishing Yield of Reef Fish</td>
<td>Non-commercial catch</td>
<td>100 m</td>
<td>Total non-commercial catch (kg/ha) of reef fish species. Derived from yearly island-scale estimates based on Marine Recreational Information Program data and mapped using the Ocean Tipping Points fishing layer methodology (McCoy et al. 2018, Wedding et al. 2018). Estimates of average annual catch were derived from Marine Recreational Information Program (MRIP) survey data and combined with measures of shoreline accessibility (terrain steepness and presence of roads) to spatially distribute catch offshore and represents the sum of all of the non-commercial boat-based and shore-based fisheries catch</td>
</tr>
<tr>
<td>Nitrogen Pollution from Golf Courses</td>
<td>Golf pollution</td>
<td>100 m</td>
<td>Nitrogen flux (kg/ha) from golf course runoff/leaching based on the total area of golf course in drainage basins (derived from USGS ArcHydro Subwatersheds/Catchments) upslope of survey sites. Golf course area was derived from National Oceanic and Atmospheric Administration Coastal Change Analysis Program and LandSat cloud-free composites created with Google Earth Engine. Golf course area is multiplied by nitrogen application rate (585 kg ha(^{-1}) yr(^{-1})) and then by a leaching rate of (32%) to estimate flux of nitrogen to the ground water. In addition, the impact on nearshore waters is reduced with distance inland of each golf course: Golf courses 0–5 km inland – 100% of leached nutrient reach the coast; 5–10 km inland – linear decay to 0 at 10 km; &gt;10 km inland – 0 nutrients reach the coast (there are no golf courses &gt;10 km inland in West Hawaii). Layer uses a Gaussian decay function with distance offshore - approaching zero at 2 km offshore</td>
</tr>
<tr>
<td>Nitrogen Pollution from OSDS and Injection Wells</td>
<td>OSDS pollution</td>
<td>100 m</td>
<td>Nitrogen flux (kg/ha) from Onsite Sewage Disposal Systems (OSDS) and Underground Injection wells within 1-yr groundwater travel time of the shoreline. Nutrient load from each OSDS is assumed to flow to the nearest point on the shoreline and then plume outward from there using a Gaussian decay function with distance from shore approaching zero at 2 km offshore</td>
</tr>
<tr>
<td>Reef rugosity</td>
<td>Rugosity</td>
<td>1 m</td>
<td>Rugosity was derived from the GAO bathymetric grids using the Benthic Terrain Modeler for ArcGIS, where the raster cell values reflected the ratio of the seascape surface area to the planimetric area determined in a 3 × 3 neighbourhood analysis</td>
</tr>
</tbody>
</table>

model where the predictor variable of interest has values equally spaced between the variable’s minimum and maximum values, and all other predictor variables were set to their means. We used the resulting output to generate smoother with the response of fish biomass shown against untransformed predictor variables.

Results

Changes in resource fish biomass across survey years

Standardized in biomass units of g/m\(^2\) and averaged within and across the survey years (2008–2018), the grazer Acanthurus leucopareius was the largest contributor to fish biomass and was the most abundant fish recorded in surveys. This species was followed by the browser Naso lituratus and the scraper Chlorurus spilurus. The fourth and fifth most abundant surveyed fish species were the scrapers Scarus rubroviolaceus and S. psittacus.

Bootstrapped estimates of confidence intervals for resource fish biomass across every year show there was significantly greater biomass of fish in 2008 (53.93 g/m\(^2\)) in comparison to 2018 (29.59 g/m\(^2\); Fig. 2). Similarly, for herbivores, browsers, and grazers, there were significantly more fish in 2008 in comparison to 2018, with the lowest biomass across surveys also recorded in 2018 (Fig. 2). For browsers, there was a fairly steady decrease in biomass, while grazers showed a significant decline in biomass between 2014 and 2018, with almost one-third of the biomass in 2018 compared to 2008 (Fig. 2). Scrapers, on the other hand, showed variable increases and decreases throughout the survey years, with the greatest biomass observed in 2014 (Fig. 2).

Effects of MPA status on resource fish biomass

Considering the full data set, the greatest biomass of fish was present in areas that banned a combination of lay nets, spears and aquarium fishing (49.26 g/m\(^2\)), with
the smallest biomass present in areas that banned lay nets only (32.88 g/m²; Appendix S1: Fig. S1). Considering the reduced data set with four different protection types, there were significant differences between protected areas across all groups of fish (Appendix S1: Table S2). For total fish, herbivores, scrapers, and grazers, post hoc tests indicated that there were significantly more fish in areas that banned lay nets, spear fishing, and aquarium fishing in comparison to those that only banned lay nets ($P = 0.011, 0.001, 0.001, \text{ and } 0.026$, respectively). Herbivores, browsers, and scrapers had significantly more fish in areas that banned lay nets, spear fishing, and aquarium fishing in comparison to those that banned lay nets and aquarium fishing ($P = 0.006, 0.023, \text{ and } 0.026$, respectively).

### Table 2. Shallow water resource fish generalized additive models (all models with weight >0.05).

<table>
<thead>
<tr>
<th>Model terms</th>
<th>Commercial catch</th>
<th>OSIDS pollution</th>
<th>Golf pollution</th>
<th>Non-commercial catch</th>
<th>Rugosity</th>
<th>df</th>
<th>Adj-$R^2$</th>
<th>$\text{AIC}_c$</th>
<th>Delta</th>
<th>Weight</th>
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**Herbivore biomass models**

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<tr>
<th>Model terms</th>
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<th>OSIDS pollution</th>
<th>Golf pollution</th>
<th>Non-commercial catch</th>
<th>Rugosity</th>
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<th>Adj-$R^2$</th>
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**Grazer biomass models**

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**Browser biomass models**

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**Scraper biomass models**

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Notes: See Table 1 for explanation of predictor variables. Note weights and variable importance are calculated from all models. Predictors included in the model are indicated by +; predictors not included in the model are indicated by NA. Adj-$R^2$ is the proportion of variance explained. $\text{AIC}_c$ is the Akaike Information Criterion corrected for small sample size. Delta is the difference in $\text{AIC}_c$ relative to the top model; weight is the Akaike weight. Variable importance is a measure of the total weight of all models containing that variable where high values (maximum = 1) are indicative of occurring in a large portion of highly ranked models where the predictor with the greatest predictive power is shown in boldface type.
respectively; Fig. 2). Significantly more grazers were also found in areas that banned spear fishing, aquarium fishing, and lay nets in comparison to full no-take regions \((P = 0.028)\).

**Modeling impacts of drivers on resource fish biomass**

A major driver of spatial variation in fish biomass across groups was nitrogen effluent from OSDS and injection wells, as it had the highest variable importance sum weight for the majority of groups and was retained in the model with the lowest AIC for all fish functional groups (Table 2). OSDS pollution was negatively correlated with all fish groups, where biomass decreased with increasing amounts of nitrogen (Fig. 3). Impacts of increasing nitrogen were similar for all functional groups except for grazers where it was fairly level; i.e., increases in nitrogen did not change grazer biomass.

The factor with the highest variable importance differed between functional groups (Table 2, Fig. 4), suggesting different pressures on each group of fish. For example, rugosity was present in most models for

<table>
<thead>
<tr>
<th>Commercial catch</th>
<th>Non-commercial catch</th>
<th>Rugosity</th>
<th>Golf pollution</th>
<th>OSDS pollution</th>
</tr>
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<td>Total fish biomass (g/m²)</td>
<td>0 1 2 3 4</td>
<td>0 1 2 3 4</td>
<td>0 50 100 150 200 250</td>
<td>0 50 100 150 200 250</td>
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<tr>
<td>Herbivore biomass (g/m²)</td>
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<td>0 1 2 3 4</td>
<td>0 50 100 150 200 250</td>
<td>0 50 100 150 200 250</td>
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<tr>
<td>Grazer biomass (g/m²)</td>
<td>0 1 2 3 4</td>
<td>0 1 2 3 4</td>
<td>0 50 100 150 200 250</td>
<td>0 50 100 150 200 250</td>
</tr>
<tr>
<td>Browser biomass (g/m²)</td>
<td>0 1 2 3 4</td>
<td>0 1 2 3 4</td>
<td>0 50 100 150 200 250</td>
<td>0 50 100 150 200 250</td>
</tr>
<tr>
<td>Scraper biomass (g/m²)</td>
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<td>0 1 2 3 4</td>
<td>0 50 100 150 200 250</td>
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→ Increasing commercial catch → Increasing non-commercial catch → Increasing rugosity → Increasing nitrogen flux from golf courses (kg/ha) → Increasing nitrogen flux from OSDS (kg/ha)

**FIG. 3.** Smoothers of predictor variables retained in the highest ranked models for resource fish biomass data grouped by various functional groups. Shaded areas show 95% confidence intervals. Data points represent fish biomass data collected from surveys during 2008–2018 for specific sites co-located with various driver data including catch values and OSDS. Fish biomass is shown on the y-axis of each plot, with the various drivers on the x-axis, with increasing values toward the right edge of each plot. OSDS, onsite sewage disposal systems.
grazers, where large increases in biomass occurred with increases in rugosity up to intermediate rugosity levels. Similar relationships with rugosity were seen for all fish functional groups. On the other hand, OSDS pollution was the most important factor explaining browser biomass, with the similar negative influences of increased nitrogen pollution correlated with decreases in browser biomass (Fig. 3). For scrapers, commercial catch was the variable with the greatest influence where scraper biomass decreased with increases in commercial catch (Table 2). When considering all functional groups of fish, except browsers for which this driver was not retained, the effects of commercial catch was highly variable and was negative for scraper biomass (Fig. 3).

The least important drivers were identified as non-commercial catch and pollution from golf courses; the variables present in the least number of models with the lowest AIC, and with the lowest variable importance across all fish functional groups (Table 2). For non-commercial catch, the relationship was almost level, i.e., biomass did not change with increases in non-commercial catch for most fish functional groups (Fig. 3). Similarly, for browsers, the relationship with golf pollution was fairly level. For grazers, biomass showed a more consistent negative relationship with increases in golf course pollution at levels greater than 40 kg/ha (Fig. 3).

**DISCUSSION**

Resource fishes in Hawaii are experiencing increasing pressure from a combination of local and global processes including fishing, habitat degradation, coastal pollution, and climate change. Our study focuses on resource species key to local subsistence and culture, contrasting the effectiveness of different MPA types as well as an in-depth investigation of the local factors that influence the near-shore resource fisheries of West Hawaii.

*Change in resource fish biomass across time*

Total resource fish biomass decreased by about 45% from 2008 to 2018. Decreases in resource fish biomass were not uniform across all fish functional groups. Browsers showed a marked decline in biomass across time, as did grazers. However, scraper biomass, which consisted of only parrotfish species in our study, was more variable over the 2008–2018 period. Interestingly, the highest scraper biomass was recorded in 2014, where scraper biomass recovery was likely assisted by the SCUBA spear fishing ban approved by the State of Hawaii Board of Land and Natural Resources in 2013 as parrotfish are primarily caught by spear fishing. After establishment of the Kahekili Herbivore Fisheries Management Area in Maui, which protects all herbivorous fishes, parrotfish biomass increased rapidly in the first 2 yr of establishment, plateauing after 3 yr (Williams et al. 2016). As 2014 surveys were completed late in the year, parrotfish would have had almost a full year to recover after the spear fishing ban was implemented. This additional form of protection could also explain why scrapers show a different pattern in population dynamics across years in comparison to other functional groups.

A global analysis of reef fish found that browsers showed the greatest declines (80% worldwide) due to their susceptibility to fishing (Edwards et al. 2014), similar to our findings here. As browsers feed almost exclusively on macroalgae and are important in preventing coral to macroalgae phase shifts as seen on the Great Barrier Reef (Cheal et al. 2013), managing the biomass of this key group of fish will be important for increasing reef resilience in Hawaii.

*Effects of marine protected areas on resource fish biomass*

The effects of MPA type were evident across all groups of fish. For all groups, there was significantly greater biomass in areas that banned spear fishing compared to areas that did not ban spear fishing. This gear ban was particularly impactful for scrapers and browsers, groups that consisted primarily of parrotfish in our study. A compilation of data across ~1,800 reef sites found that for parrotfish, fishing restrictions (gear and access limitations) provided the same conservation gains as fully protected MPAs (Cinner et al. 2020) and thus for this particular group of fish, gear restrictions can be very effective.

For grazers, there was significantly greater biomass in areas that banned multiple gear types when compared to full no-take areas. Similarly seen across all fish functional
groups, the greatest biomass occurred in MPAs that banned lay nets, spears, and aquarium fishing, although not statistically significant for all groups. Our results suggest that banning gear types could be effective for protecting fish biomass in this region. This is similar to a recent analysis of MPAs in Hawaii that showed both full and highly protected (typically limited to pole and line fishing) MPAs had greater fish than in areas of low or intermediate protection (Friedlander et al. 2019). A global synthesis of the effectiveness of MPAs showed that the positive response to protection was primarily driven by targeted fish species (Seiberras et al. 2013). Four of the five most abundant species from the surveys are primarily caught by spear (Appendix S1: Table S1), which helps to explain why MPA types that ban this gear type had greater resource fish biomass in our analyses.

There is considerable evidence that supports that coral reef fishes will recover with reductions in fishing pressure (Campbell et al. 2017). It is important to note, though, that for our study, there were very few sites representing no-take areas, with some fully protected no-take areas only recently established in West Hawai‘i as late as 2016, where prior to 2016, there were only two full MPAs protecting only a small combined area of ~0.6 km$^2$ (Friedlander et al. 2019). Long-term observations of no-take MPAs have shown that effects of MPA establishment can occur within 5 yr but can still take a decade or more to fully develop (Babcock et al. 2010, Friedlander et al. 2019). Thus, the true impacts of no-take areas might not be realized in this study.

The establishment of MPAs can be contentious. Although no-take areas can provide the greatest conservation gains (Cinner et al. 2020), specific gear restrictions may be a socially relevant management strategy in Hawaii that will also support recovery of resource fish biomass (Weijerman et al. 2018). For example, in some regions across Hawaii, permitting only line fishing allowed a balanced trade-off between various stakeholders as well as enhancement of reef recovery (Weijerman et al. 2018).

Drivers of resource fish biomass

Nitrogen input from OSDS was the dominant driver of changes in resource fish biomass in our study. The impacts of OSDS nitrogen effluent differed between fish functional groups, which is especially evident when herbivores were divided into grazers, browsers, and scrapers. Understanding the impacts of drivers on grazers (primarily surgeonfish in these surveys) and scrapers (primarily parrotfish) is important because they have disproportionately large effects on reef processes (Bellwood et al. 2006, Lokrantz et al. 2008). In Hawaii, OSDS are common and are known to contaminate both drinking water and nearshore waters (Swarzenski et al. 2016). Due to Hawaii’s volcanic geology, sewage can penetrate the porous surfaces and contaminate groundwater, where the main wastewater nutrient discharged to reefs is nitrogen (Hunt and Rosa 2009, Barnes et al. 2019). Land-based pollutants disrupt normal reef functioning, where elevated nutrient concentrations create additional stress for corals, inducing negative responses such as decreased reproduction and calcification (Loya et al. 2004, Fabricius 2005, Wiedemann et al. 2013, Carlson et al. 2019). In Fiji, terrestrial run-off affected the hard-bottom benthic habitat, ultimately leading to a decline in fish biomass (Brown et al. 2017). Thus, these deleterious effects on corals likely have cascading impacts on reef fish via habitat alteration (Komyakova et al. 2013).

The State of Hawaii plans to eliminate cesspools by 2050 (DOH 2018), where cesspools, a form of OSDS, consists of raw sewage in underground wells, leaching raw wastewater into groundwater. Further research investigating the prioritization of cesspools to upgrade and minimize pollution as done in West Maui (Barnes et al. 2019) would be valuable for West Hawai‘i, especially to reduce the impact of nitrogen input on resource fish biomass. The influences of nitrogen input from golf courses on resource fish biomass were not as important in our results, likely because nitrogen levels from the golf courses were 10× lower than OSDS levels. However, there were still negative impacts of this driver on grazer biomass at higher levels of nitrogen runoff.

These findings suggest that land-based sources of pollution (LBSP), and more specifically, eutrophication of nearshore coastal waters from OSDS and local injection wells, negatively impact local fish populations. This may mean that current state water quality standards, as advised by The Hawaii Department of Health’s Clean Water Branch, are not sufficient to ensure the biological integrity of coral reef ecosystems in West Hawaii. Working in concert with groups such as the Hawaii Department of Land and Natural Resources to appropriately manage LBSP will be especially important for browsers, the functional group for which OSDS was the most dominant driver of biomass. The initiatives and actions planned in the 2030 Hawaii Coral Reef Strategy (The State of Hawaii 2010) that directly address LBSP will be important to prioritize.

Across all groups except scrapers, biomass increased with increasing reef rugosity. Grazer biomass showed the strongest positive relationship with rugosity. It is likely that increased availability of three-dimensional habitat space is especially important for grazers, e.g., by providing predator refuge for species such as A. lueccopareus and A. guttatus (González-Rivero et al. 2017). On the other hand, for scrapers, commercial fishing pressure showed the strongest effects, whereby increased commercial activity caused significant declines in scraper biomass. In 2018, total parrotfish (scraper) commercial catch was 70% of total surgeonfish (grazer) catch (Division of Aquatic Resources 2018). Since scrapers show a decline with increasing commercial catch while grazers initially show an increase, and only decreases when a higher threshold is reached (2 kg/ha), the level of fishing pressure that drives negative changes in biomass appears to be different based
on the functional group. Current commercial fishing levels may not be supporting sustainable scraper populations. This finding highlights the importance of considering driver impacts on fish by their functional group to be able to implement effective management strategies most relevant to that specific group.

Commercial catch more strongly impacted resource fish biomass than non-commercial catch. This is surprising because non-commercial catch is an order of magnitude greater than commercial catch in our model, and the annual value for non-commercial, near-shore fisheries in Hawaii is estimated to be $7.2–12.9 million, much higher than the annual value for commercial near-shore fisheries ($2.97 million licensed + $148,500–$445,500 unlicensed; Grafeld et al. 2017). Our commercial information was derived from reported catch numbers across large spatial commercial reporting blocks, while non-commercial fishing was derived from downscaled island-wide catch estimates based on proxies such as shoreline access and distance to boat ramps. This suggests that more accurate and detailed data on fishing pressure, such as mandatory reporting for non-commercial catch, would undoubtedly improve our results and the ability to assess the relative role of commercial and non-commercial fishing pressure on resource fish biomass.

Our highest performing models explained 26% of the total variance, indicating that there are other factors impacting resource fish biomass remaining to be included in future studies of West Hawai‘i resource fish communities. Information on ocean conditions, such as wave action and ocean temperature, were not included, which may be affecting fish biomass and could account for the limited variance explained by the models. Increased frequency in warming events and resulting coral bleaching has likely contributed to decreases in total fish biomass, where ocean warming has driven declines in fisheries globally with negative effects exacerbated in regions with a history of overfishing (Free et al. 2019). In 2015 in Hawaii, the warmest year on record, 30–50% of coral cover was bleached in West Hawai‘i (Kramer et al. 2016; Gove et al. 2019). As live, healthy coral cover is linked with greater fish abundance (Jones et al. 2004, Komyakova et al. 2013), the 2015 warming event in conjunction with coral death likely contributed to the decline seen for resource fish between 2014 and 2018.

Despite these caveats, our findings for West Hawaii suggest that banning specific gear types can be effective in protecting shallow water resource fish biomass. Furthermore, we find that impacts of nitrogen pollution on resource fish biomass can outweigh other habitat and land-use drivers; however, the effects are specific to particular functional groups of resource fish. Current commercial fishing levels are negatively affecting scraper populations, which suggests that limits on commercial catch of scrapers could help to enhance local populations. All these examined factors interact and exacerbate the negative impacts of climate change on coral reefs, where mitigation of local stressors can help to compensate for impacts of global stressors (Brown et al. 2013, Harvey et al. 2018). Our observations suggest that regional management of multiple stressors would be beneficial in enhancing resource fish biomass in West Hawaii, contributing to increased reef resilience and recovery.

Acknowledgments

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Literature Cited


Sala, E., and S. Giakoumi. 2018. No-take marine reserves are the most effective protected areas in the ocean. ICES Journal of Marine Science 75:1166–1168.


SUPPORTING INFORMATION

Additional supporting information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/eap.2213/full

DATA AVAILABILITY

Data are available from the Zenodo Digital Repository: http://doi.org/10.5281/zenodo.3901864