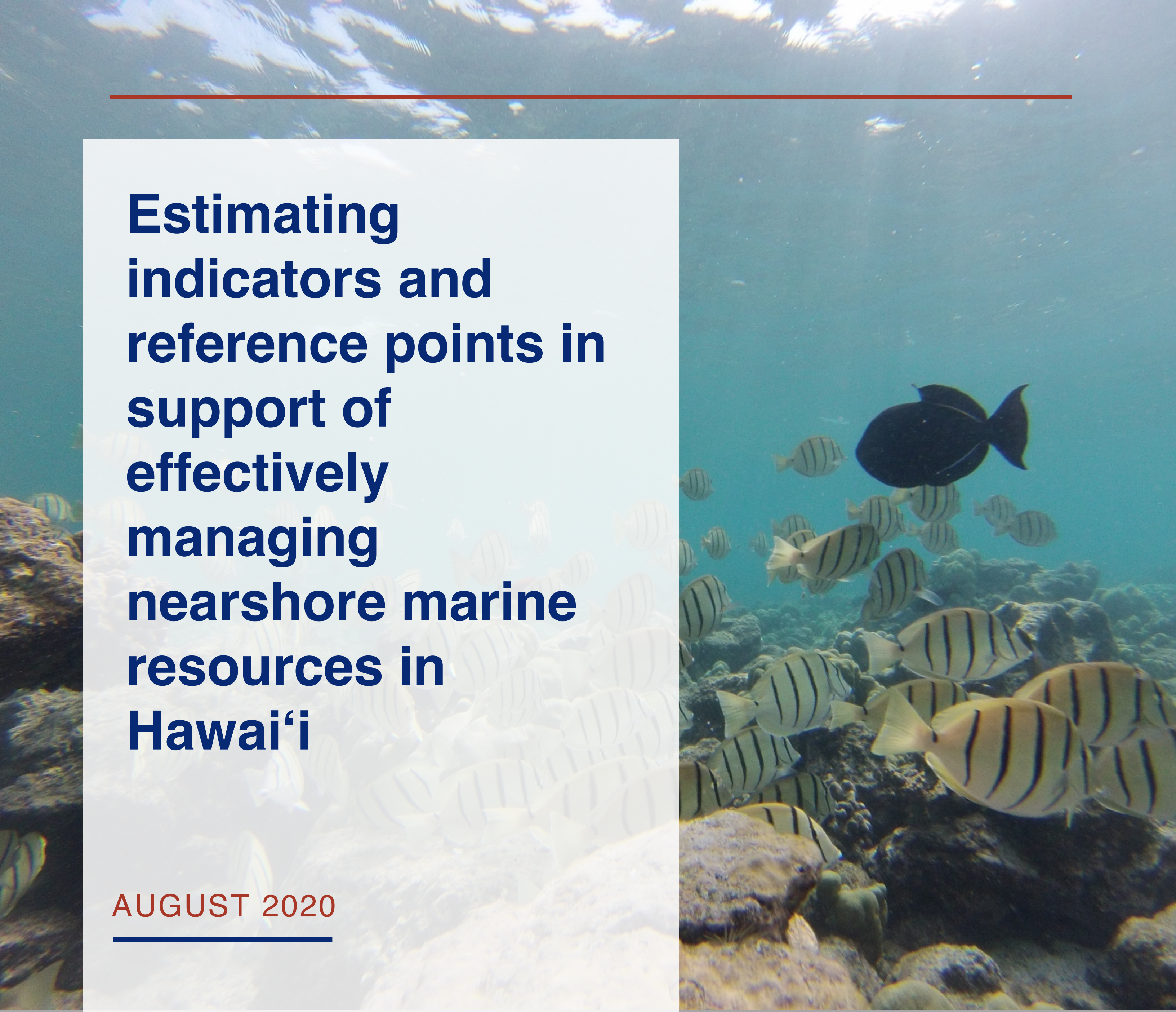

Estimating indicators and reference points in support of effectively managing nearshore marine resources in Hawai‘i

AUGUST 2020

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Hawai‘i Monitoring and Reporting Collaborative
HIMARC

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Executive Summary

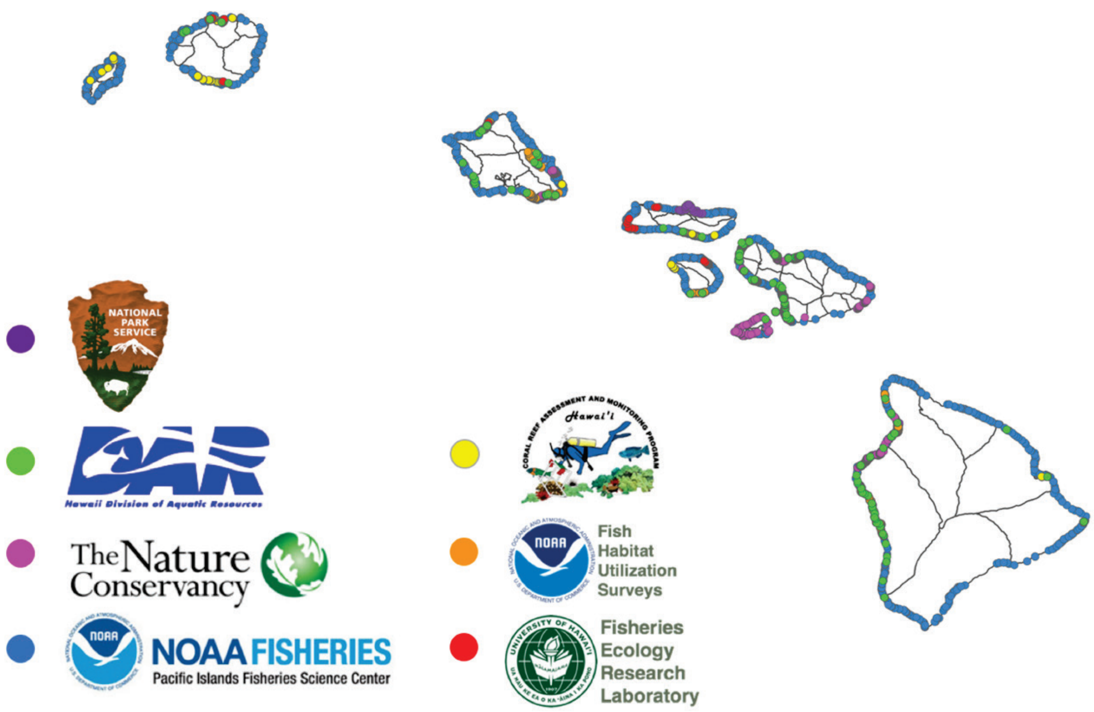
Project Objectives

The objectives of this project were to develop a rigorous and transparent analysis of ecological indicators than can be used to **measure the condition of nearshore ecosystems in Hawai‘i** and to **identify areas most likely to benefit from management**.

To achieve this objective, we conducted work in 4 phases:

Synthesizing existing data

Seven major monitoring programs conduct surveys of fish and benthic assemblages of coral reef ecosystems in Hawai‘i.



Locations of underwater visual surveys are depicted with dots across the State of Hawai‘i. Colored dots correspond to the monitoring program that conducted the survey.

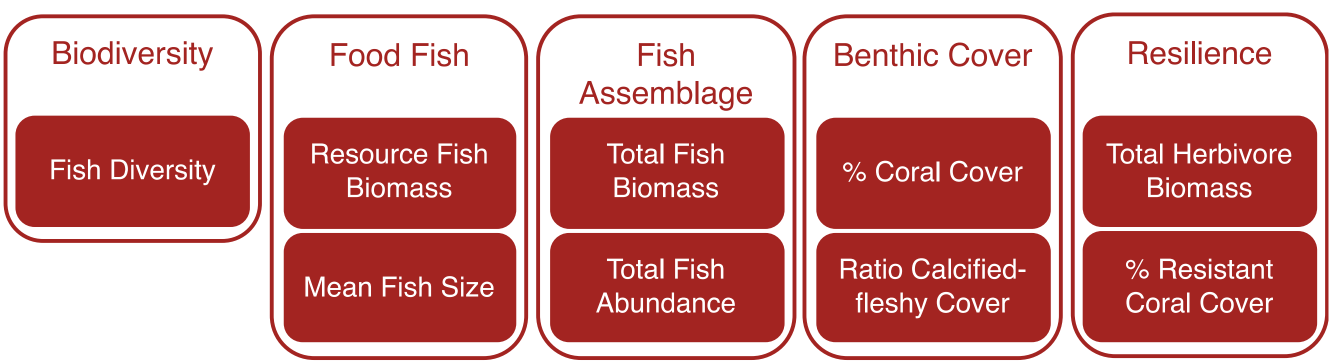
These disparate datasets were compiled into a single database to conduct synthetic analyses across different components of the coral reef assemblage. This was accomplished by developing an interactive process for data integration with partner organizations that included careful quality control of the data and resulted in increased value of the individual and combined datasets.

Together the database includes 7240 benthic replicates and 8900 fish replicates spanning 1993 to 2016. The majority of the data (98%) were collected between 2000 and 2016. Data are spatially comprehensive, with few areas with no surveys. Several locations have been more densely sampled than others including Maunalua-Hanauma Bays, Kāneʻohe, Pūpūkea-Waimea, Kalaupapa, West Maui, and West Hawaiʻi.

Select indicators

Following a systematic review, 28 candidate indicators were identified and then scored according to established criteria. The criteria were related to 1) the theoretical soundness, 2) relevance to management concerns, 3) known responsiveness to management interventions, 4) data availability and measurability, and 5) interpretability by policy makers and the public. Stakeholder input was gathered at multiple steps in the process.

Ultimately, 9 indicators across 5 categories were selected to represent 5 aspects of the condition of nearshore resources:



Estimate Condition

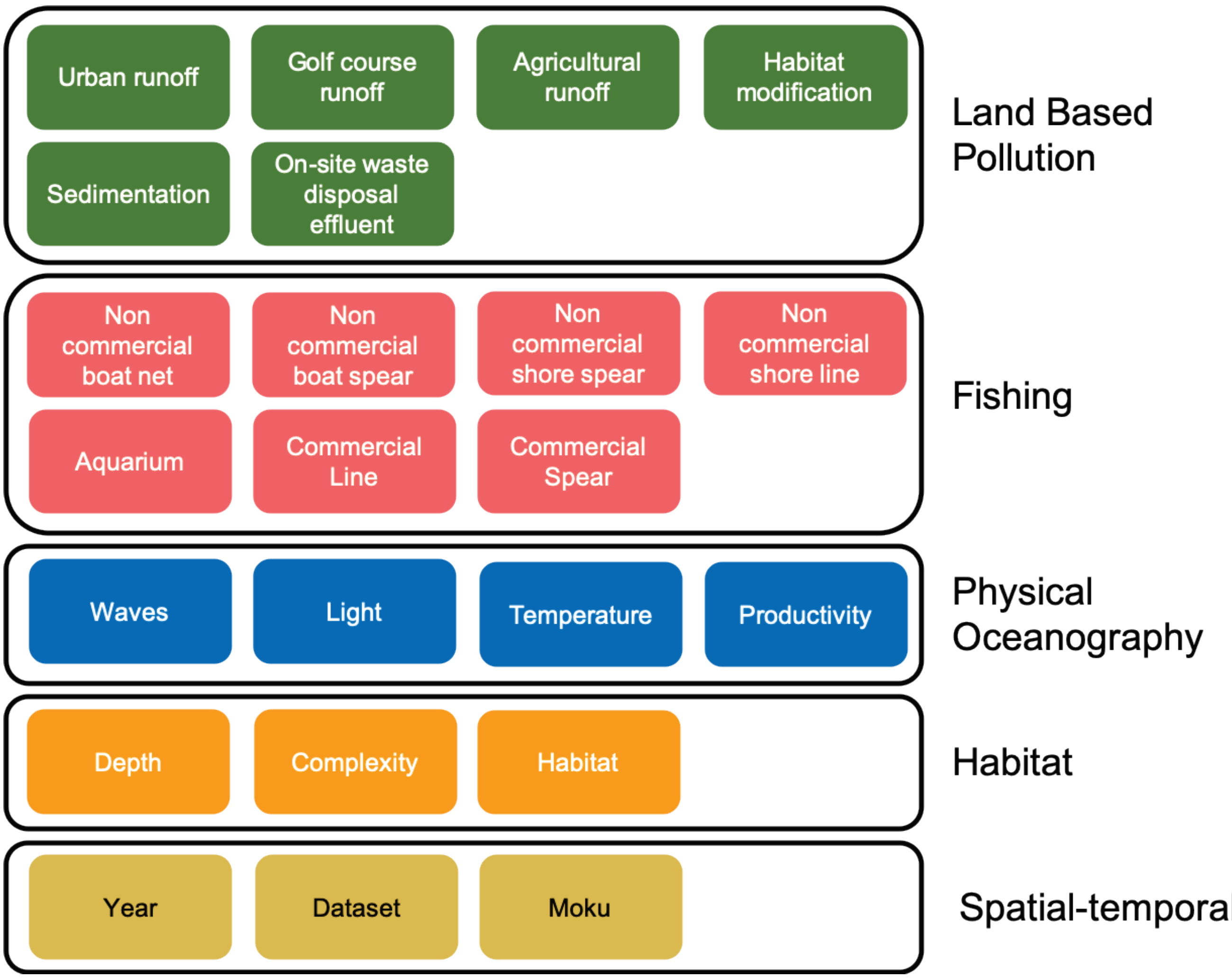
For each indicator, we estimated observed condition using hierarchical Bayesian models that accounted for variation in space, time, and data source, and were a function of human and environmental variables.

Comparison of reefs in different condition. Reef on the left that has been impacted by humans compared to reef on the right that is relatively intact. Left photo: NOAA, Right photo: Catlin Seaview.

As part of the modeling process, we considered how to achieve the most robust and relevant estimates of reef condition given the available data. During this process, we developed recommendations for how to account for variability in survey design in the combined HIMARC dataset, including appropriate methods for hierarchical modeling.

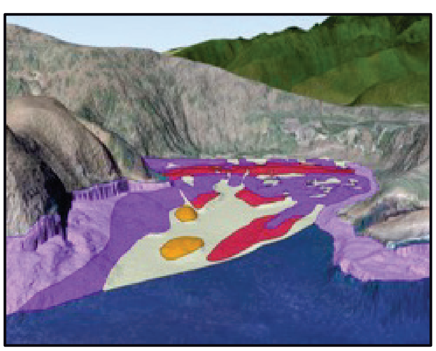
The motivation for this decision was to capture the condition of Hawaiian reefs prior to the 2014-2015 marine heatwave that caused widespread coral bleaching and subsequent mortality. Thus, the products generated here provide insight into the condition of reefs before this pulse event and will allow us to make meaningful inferences of how that event shaped Hawai‘i’s reefs in future analyses of change over time. In doing so, it forestalls a ‘sliding baseline’, where already-degraded reefs become normative. Importantly, the 2004-2014 period includes ~8000 observations that, together, form a spatially comprehensive and representative set.

Our hierarchical modeling framework was customized to meet our project objectives, given the inherent variability of underwater survey. Further, our approach included accounting for ‘unbalanced’ data – where data are not evenly spread across habitat type, depth, or other important strata. Each indicator was estimated with hierarchical models that accounted for variability due to differences in the sampling methods of each monitoring program, time, and space, and post-stratified to appropriately weight predictions in space.



Predictors included in models of indicator condition and recovery potential include anthropogenic inputs, oceanographic variables, and habitat characteristics.

Each indicator was modeled as a function of a set of anthropogenic, oceanographic, and habitat predictors. Existing spatial data for oceanographic and human drivers were available from the Ocean Tipping Points Project (oceantippingpoints.org/Hawaii) (Wedding et al. 2018). For habitat layers, we relied on habitat maps produced by NOAA's Biogeography Branch (Battista et al. 2007). For bathymetric data, due to significant gaps in previously available remotely sensed sources, we undertook an effort to combine three data sources: 2000 and 2014 LiDAR from the Army Corps of Engineers, and imaging spectroscopy-derived data provided by Arizona State University's Global Airborne Observatory (Asner et al. 2020).



- **Non-commercial boat-based net fishing** had a consistent and large negative effect on all fish indicators. **Non-commercial boat and shore-based spear fishing** also both had a consistent negative effect on all fish indicators except for fish diversity.

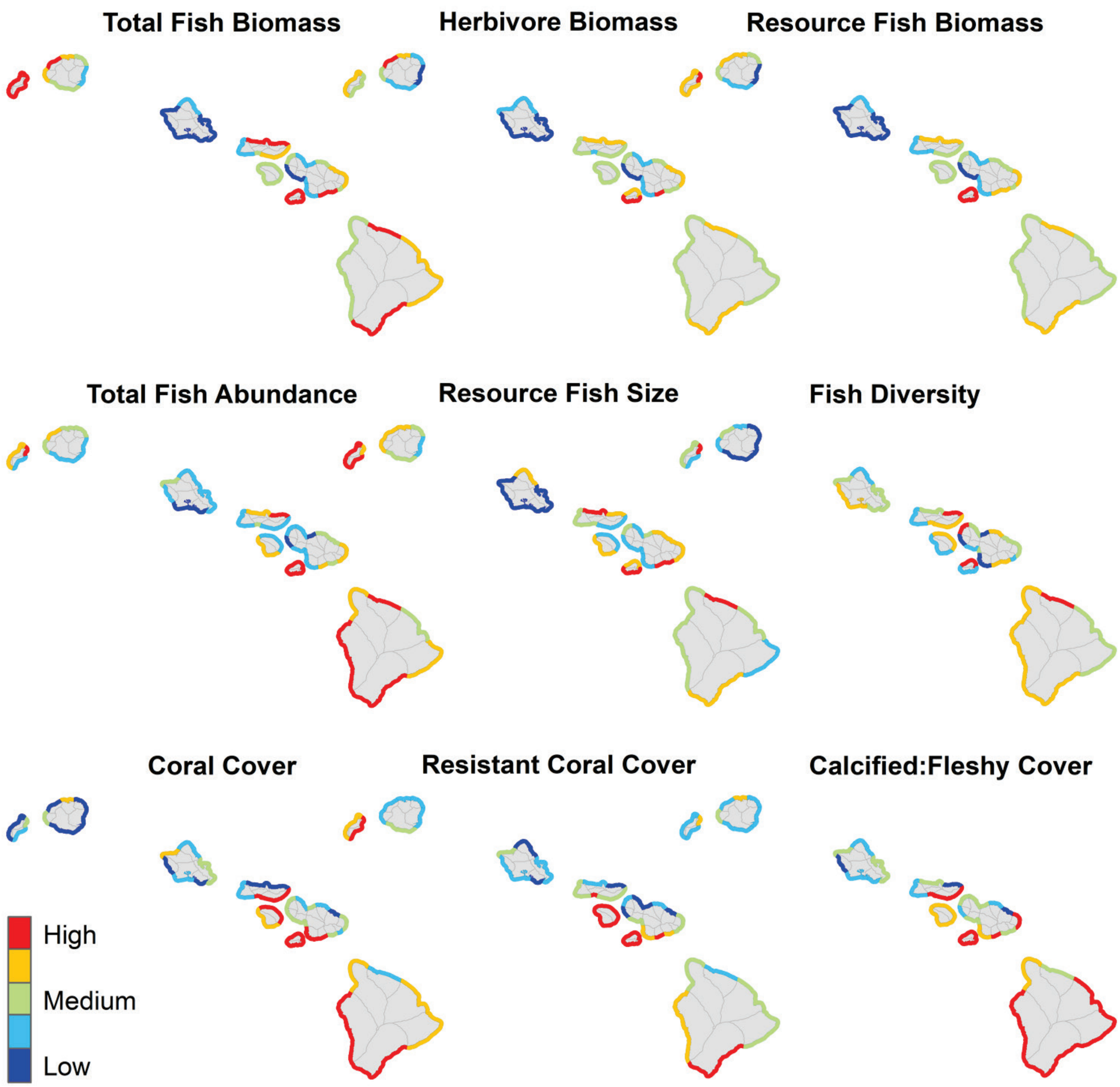
- **Herbivore biomass** had a consistent and large <u>positive</u> effect on benthic variables.

- Negative effects of **land-based pollution** were evident for fish indicators and less conclusive for benthic indicators. Onsite waste disposal effluent and habitat modification negatively affected fishes.

- Oceanographic and habitat variables were important across all indicators, underscoring the necessity of accounting for these effects when interpreting patterns of human impacts in Hawai'i.

Photo credits: (Top) Forest & Kim Starr, Wikipedia Commons, (Upper Middle) KITV, (Lower Middle and Bottom) Kosta Stamoulis

At the scale of moku, there was large variability across the nine ecological indicators. Moku are a sub-island delineation used traditionally in Hawai‘i for biocultural resource management (Malo 1951, Winter et al. 2018).



Moku-scale average condition for each of nine indicators. These values were calculated by using all available survey data to estimate drivers of condition, predicting condition based on spatially-explicit driver values across all moku, and summarizing the condition at the moku scale. Condition is presented using a color scale from high values (red) to low values (blue). Values for each indicator are relative to the values of that indicator across the other moku within the State of Hawai‘i.

- Some moku were consistently high across all indicators, such as Kahoʻolawe and Kaʻū Hawaiʻi.
- Others had high values for fish related metrics, but varied in benthic cover, such as Niʻihau and Koʻolau Molokaʻi.
- Several moku were low across all indicators including Kona and Ewa Oʻahu and Lahaina Maui.
- With a focus on resilience indicators, Kona Kahoʻolawe, Koʻolau Kahoʻolawe, Hana Maui, and Hāmākua Hawaiʻi ranked the highest, while all of the lowest were all on Oʻahu, including Waiʻanae, Kona, and Ewa.

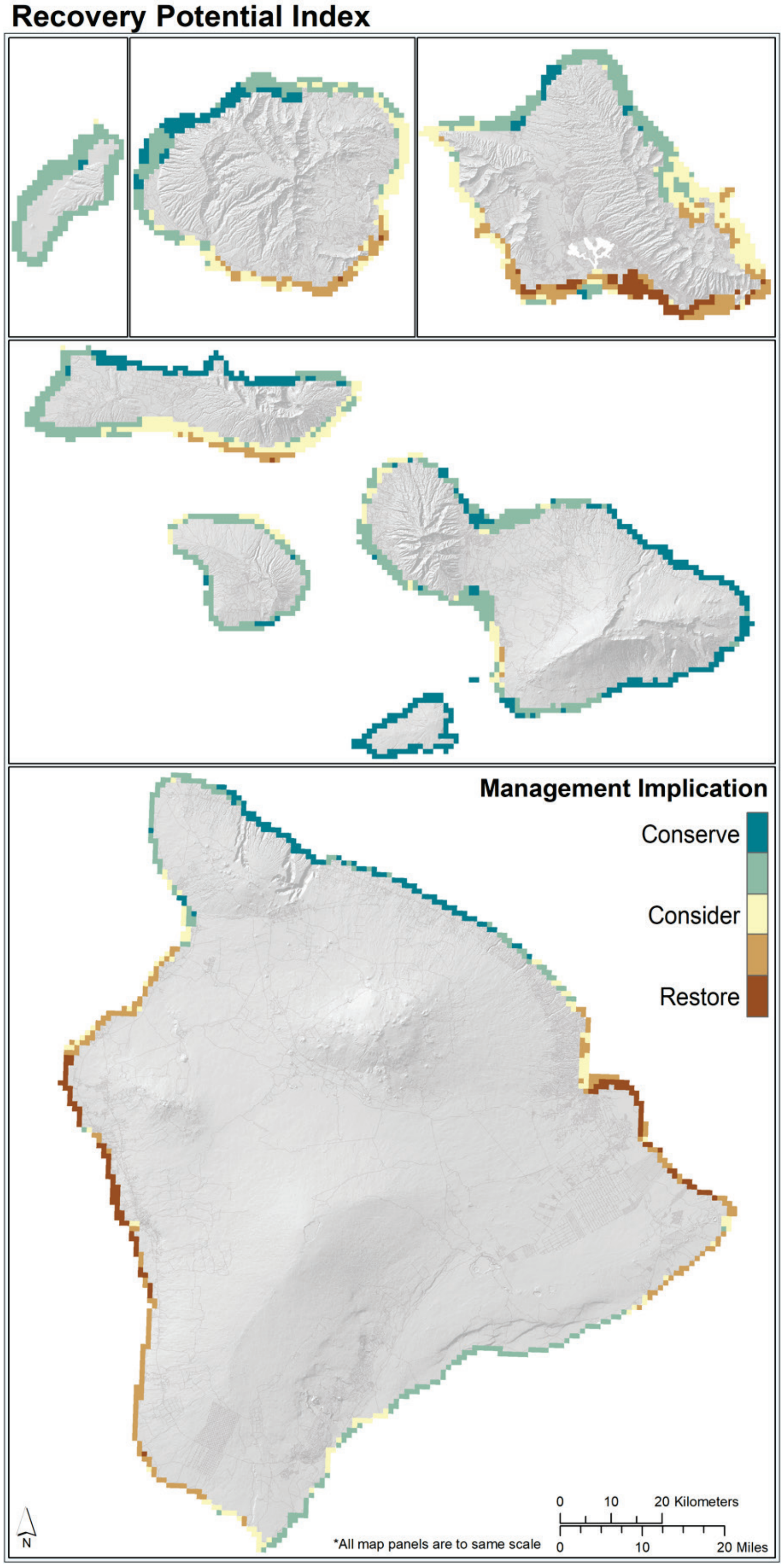
Detailed maps of each indicator are provided in Appendix 3.

Modeling Recovery Potential

In order for indicators to inform management actions they need to be put in context of values that are expected under different circumstances. For example, we might expect that coral cover is lower in places that experience large wave events compared to more sheltered environments. We used this thinking to develop maps of *recovery potential* – the difference between the current condition of a site and its *potential* condition when human impacts are reduced.

> ***Recovery potential*** **– the difference between the current condition of a site and its *potential* condition when human impacts are reduced**

Recovery potential was estimated by comparing maps of observed condition from the previous step to predicted maps where human impacts were minimized. That is, by accounting for variation in factors over which humans have little or no control (e.g., oceanographic and habitat variables), we isolate the effect of human impacts and identify areas that will be most responsive to management actions.



- Reducing human impacts in South O‘ahu, South Kaua‘i, South Moloka‘i, and East and West Hawai‘i could result in improvements across all indicators.

- Human impacts did not reduce conditions on remote, north facing shorelines, implying that effective management in these areas will conserve conditions.

- East Kaua‘i, Wai‘anae, Ko‘olaupoko, South Moloka‘i, West Maui, and Kihei Maui had mixed effects of human impacts, so further consideration of individual indicators will determine what actions will lead to effective management.

Maps of Recovery Potential for each indicator independently are provided in Appendix 4.

A combined index of recovery potential for a 9 indicators is shown at the 1-km resolution across nearshore habitat in the State of Hawai‘i. Green corresponds to locations where the current condition is similar to the predicted condition if human impacts were decreased. High recovery potential (red) corresponds to locations where the current condition is substantially lower than the predicted condition if human impacts were decreased.

Table of Contents

EXECUTIVE SUMMARY 3

Project Objectives 3

Synthesizing existing data 3

Select indicators 4

Estimate Condition 5

Modeling Recovery Potential 9

TABLE OF CONTENTS 11

INTRODUCTION AND BACKGROUND 13

SYNTHESIZING EXISTING DATA 14

SELECT INDICATORS 17

Candidate indicators 17

Evaluate and score indicators 18

Assess data quality 19

Final indicator set 19

ESTIMATE CONDITION 23

Identifying data gaps and their influence on estimates 23

Compiling predictor layers 26

Modeling framework 30
Model Details 31
Spatial presentation of model results 32
Sources of uncertainty and spatial variation 34

Indicator condition 36

MODELING RECOVERY POTENTIAL 39

Interpreting recovery potential 40

Recovery potential – results 42

APPLICATIONS TO MANAGEMENT 43

Documenting conditions 43

Identifying areas most likely to benefit from management 43

Identifying specific and measurable targets 44

Evaluating outcomes after management actions are taken 45

NEXT STEPS 46

Data integration moving forward 46
Continued improvement and institutionalization in dataset comparability through capacity building 46
Calibration update 46
Memorandum of understanding for HIMARC partner organizations 47

Applications to management 48
Furthering our understanding of human impacts on indicator condition 48
Overlaying climate change 48
Management planning through scenarios 49
Evaluating outcomes after management actions are taken 49

REFERENCES 50

APPENDIX 1 – DATA INTEGRATION PROCESS 59
A. Data Request 59
B. Data Formatting and QAQC 59
C. Discuss Data QAQC Report with Data Partner 63
D. Share HIMARC Formatted Dataset with Data Partner 63
E. Merge QAQCed and Formatted Datasets into HIMARC Database 64
F. Calibrate Across the Distinct Survey Methods for Fish Surveys 64

APPENDIX 2 – INDICATOR SELECTION DATA 66

APPENDIX 3 – INDICATOR CONDITION MAPS 78

APPENDIX 4 – RECOVERY POTENTIAL 86

Introduction and Background

Coral reef managers are frequently tasked with addressing multiple threats to the ecosystem resulting in a need to prioritize management actions. Once action is taken, managers require metrics to understand the effects of their actions and to measure progress towards management goals. Ecological indicators can address these needs by measuring current conditions, prioritizing areas most likely to benefit from management, identifying specific and measurable targets, and evaluating outcomes after management actions are taken.

We developed ecological indicators for nearshore ecosystems in Hawaiʻi by compiling existing data from underwater visual censuses of fish and benthic assemblages as part of the Hawaiʻi Monitoring and Reporting Collaborative (HIMARC). The organizations that are part with the Collaborative include State of Hawaiʻi Division of Aquatic Resources (DAR), University of Hawaiʻi (UH), The Nature Conservancy (TNC), National Park Service (NPS), NOAA PIFSC Ecosystem Science Division, Hawaiʻi Coral Reef Monitoring Program (CRAMP), NOAA Biogeography Program, Western Pacific Fishery Management Council, Conservation International Hawaiʻi, NOAA Pacific Island Region Office, and the Center for Global Discovery and Conservation Science at Arizona State University (GDCS).

The wealth of information from the synthesis of underwater visual surveys in Hawaiʻi was used to address the overall objective, which was **to develop a rigorous and transparent analysis of ecological indicators than can be used to measure the condition of nearshore ecosystems in Hawaiʻi and to identify areas most likely to benefit from management.**

To meet this objective, the project included four activities:

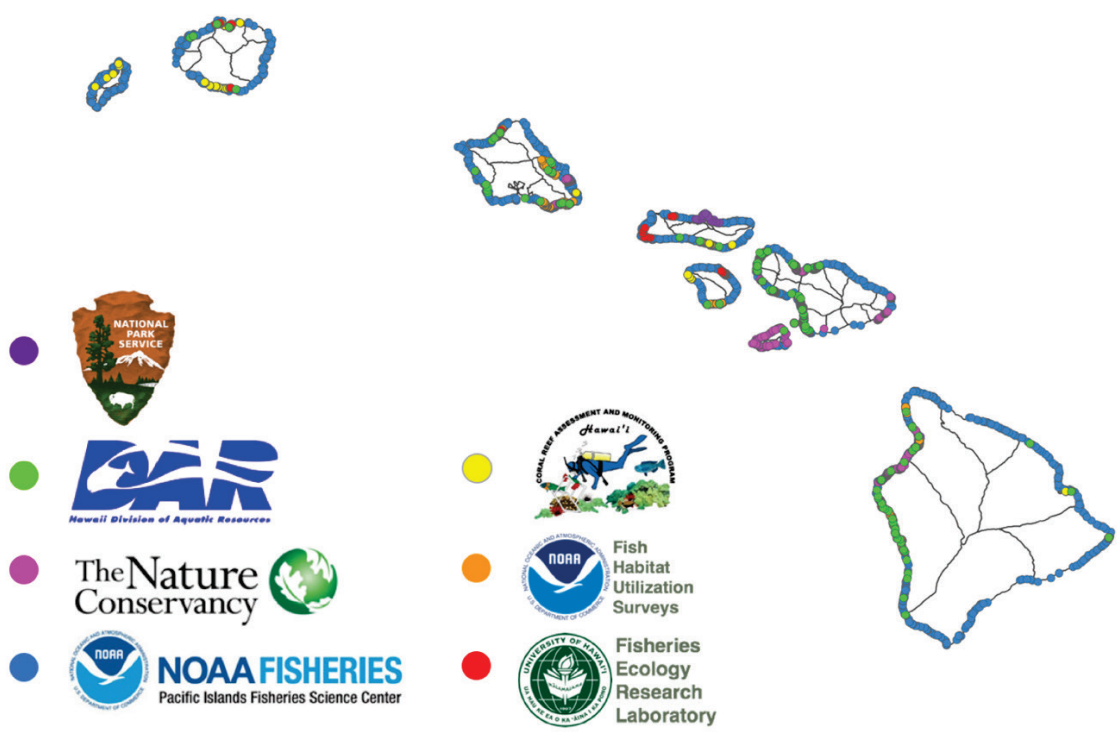
1. <u>synthesize existing data</u> to build the HIMARC database,
2. <u>select indicators</u> based on a systematic review,
3. <u>estimate condition</u> of each indicator, and
4. <u>model recovery potential</u> to provide a measure for ‘effective management’.

Synthesizing existing data

Seven monitoring programs conduct surveys of fish and benthic assemblages of coral reef ecosystems in Hawaiʻi, with a variety of underwater survey techniques. These are:

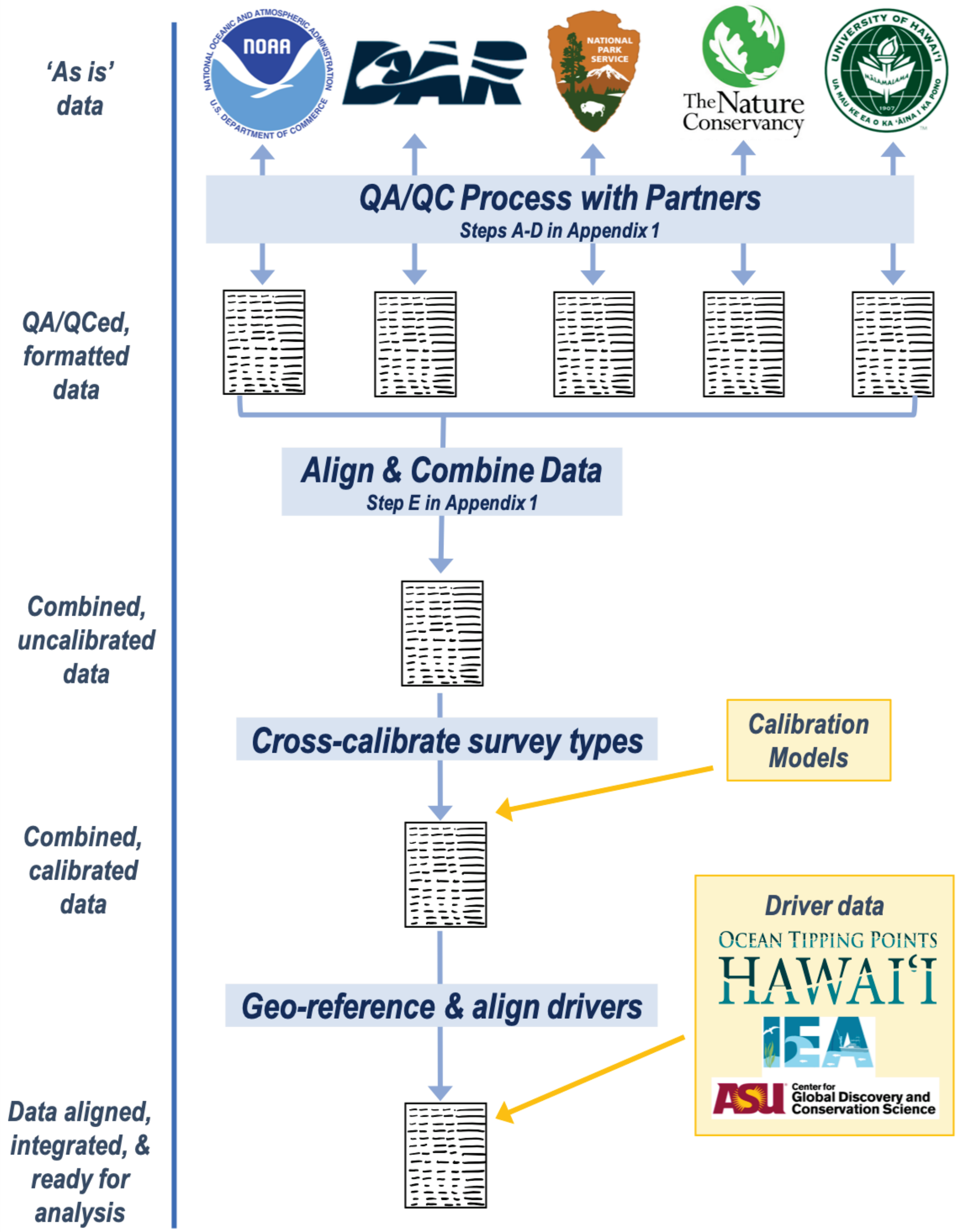
- State of Hawaiʻi Division of Aquatic Resources (DAR),
- The Nature Conservancy (TNC),
- National Park Service (NPS),
- NOAA PIFSC Ecosystem Science Division,
- Hawaiʻi Coral Reef Monitoring Program (CRAMP),
- NOAA Fish Habitat Utilization Study, and
- University of Hawaiʻi Fisheries Ecology Research Lab (UH).

The data were first integrated in 2012-2013, and were updated in 2016, and again in 2020. In total, the database consists of over 10,000 replicates spanning 1993 to 2019. Data are spatially comprehensive, with few areas with no surveys.



Locations of underwater visual surveys are depicted with dots across the State of Hawaiʻi. Colored dots correspond to the monitoring program that conducted the survey.

A founding goal of HIMARC was to integrate underwater visual survey data of reef fish and benthic cover from multiple partner organizations around the state so that management decisions could be based on all available data. Each partner organization uses slightly different methods to collect their data, different formats and software platforms to enter and store their data, and varying degrees of internal QAQC.



To effectively compile these data into a single database, data shared with HIMARC by partners is:

(1) reviewed to ensure clear interpretation of the original data and overall structure of the survey design,
(2) transformed into a consistent format, which was intentionally designed to retain key features of the original data structure,
(3) run through a thorough quality control process to identify any missing data, potential errors, and duplicated data, and
(4) integrated into the HIMARC database framework.

In an effort to improve this process, we developed a quality-assurance-quality-control (QAQC) protocol and associated programming scripts to encourage two-way conversations between HIMARC and each of the data providing partner organizations. This process was designed to engage data partners in the integration process, to clarify questions about each organization's data formatting, to identify potential errors in the data as provided, to correct errors in coordination with the partner organization, and to strengthen conversations and relationships related to data collection, data sharing, and data QAQC. As added benefits, these conversations build capacity for database formatting and QAQC within the data partner organizations, clarify the nuanced steps and potential impediments between field data collection and statewide analyses, and establish a connection for sharing datasets (both the original datasets held by partner organizations and the HIMARC formatted datasets) and QAQC protocols and scripts. The QAQC process can be time-intensive and requires dedicated personnel; it is detailed in Appendix 1. A key next step in advancing statewide management and monitoring goals is to leverage the process developed here to improve the QAQC capacity within each partner organization, reduce the time and cost of data integration, and, ultimately, institutionalize this task.

Select indicators

Indicator selection was an iterative process: potential indicators were identified from a literature review and reviewed by an advisory team consisting of HIMARC partner organizations; proposed indicators were evaluated, scored, and prioritized by using established criteria; and final indicators were reviewed and decided by the HIMARC partner organizations.

Process for selection indicators of reef condition. At each step results and decisions were reviewed by an advisory team from HIMARC's partner organizations.

Candidate indicators

Indicators of interest were identified by conducting a literature review and evaluating each candidate indicator systematically against a set of criteria before selecting a final set of candidates. Candidate indicators including those cover the fish assemblage and benthic cover (e.g., total fish biomass, coral and macroalgal cover). Additionally, those that to biodiversity and resilience, and metrics related to food fishes (e.g., resource species).

A total of 28 indicators were identified as candidates that were possible to estimate from the database (Appendix 2). Additional candidate indicators that were identified in the literature but could not be estimated from the combined state-wide data included terminal phase parrotfish presence, coral size frequency, coral health (bleaching, disease, etc.), coral cover by growth form (branching, plating, mounding), urchin density, urchin species composition, and connectivity.

Evaluate and score indicators

Multiple frameworks exist for evaluating candidate indicators systematically based on a defined list of criteria (Kershner et al. 2011, Boldt et al. 2014, Holsman et al. 2017). Building from these existing frameworks, a set of criteria were used to evaluate each indicator in terms of the suitability for inclusion in the analyses:

Measurable with existing database – Is it possible to estimate the metric with currently available data?
Theoretical soundness – evidence exists that justifies the indicator as a measure of ecosystem status and trends and/or as a proxy for effects of human influences on the ecosystem.
Relevance to management concerns – the indicator is directly related to one or more objective or action of the planning activities.
Known responsiveness to management interventions – the indicator has been used previously to detect change as a response to a management action or other reduction in human-induced pressure.
Interpretability by policy makers and public – indicators should be simple to interpret, communicate, and understand without prior knowledge or background.

Each candidate indicator was systematically evaluated against the criteria above and scored by examining peer-reviewed literature and reports (Appendix 2). Given that the indicator was not immediately relevant to the planning process if the data were not available, this criterion was given the highest weight; i.e., further evaluation was not considered if the indicator could not be measured. The other four criteria were scored as: 1: supported by peer-reviewed publications that provide consistent and strong findings; 0.5: limited support from peer-reviewed publications or expert input; 0: no peer-reviewed evidence, or conflicting evidence available.

The final score based on the literature for each indicator was then calculated by combining all of the criteria as follows:

$$X_1 * \frac{\sum_{i=1}^{n} X_i}{n}$$

where X_1 is either 0 or 1 and indicates whether data are available to estimate the indicator, and X_i are the remaining criteria listed above. Thus, the indicator will have a non-zero score when data is available that is the average of the scores for criteria with existing evidence. Only scores greater than 0.5 were considered further to ensure adequate support from the literature.

Assess data quality

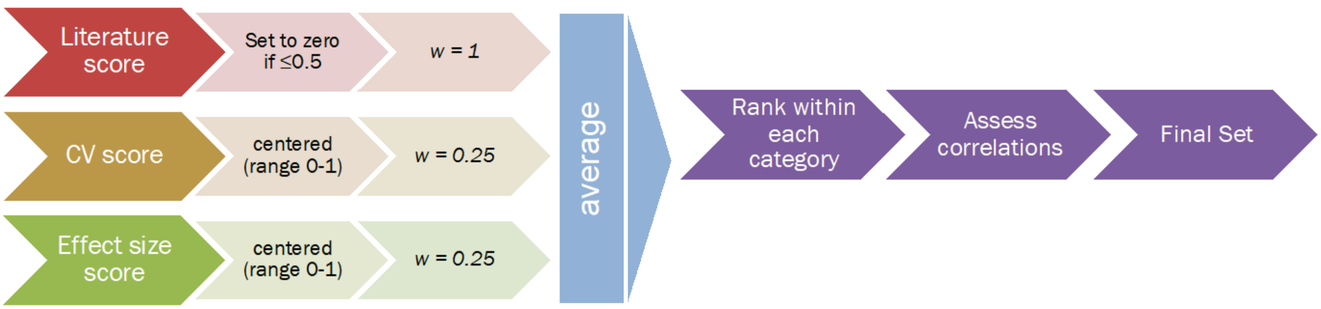
To further refine the indicator set, we also considered aspects of the data quality. Specifically, we assessed 1) dispersion of the sample means as a function of sample size, 2) effect size, and 3) correlation among indicators. The dispersion of sample means as a function of sample size was assessed as a measure of within moku variability. We calculated the coefficient of variation (CV) of sample means (standard error/mean) for each moku and plotted it against sample size for that moku. We then fitted an exponential linear model to the relationship between CV and sample size and calculated the predicted CV at 30 samples ($CV_{n=30}$), which is roughly the 25% quantile for sample sizes by moku for both fish and benthic datasets. Thus, $CV_{n=30}$ represents the amount of within-moku variation for each indicator scaled to the same sample size. Effect size was measured for each indicator as the difference in between the mean of the moku at the 80% quantile of all moku and the mean of the moku at the 20% quantile, divided by the standard error of the moku at the 80% quantile. Thus, effect size compares how well the indicator can differentiate between moku (by comparing between-moku variation after normalizing for within-moku variation). Both $CV_{n=30}$ and effect size were scaled to range from 0 to 1. Finally, we calculated Spearman correlation coefficients for each combination of indicators across the whole dataset to assess whether particular indicators could be redundant. We considered indicators to be highly correlated if the correlation coefficient was greater than 0.7.

Final indicator set

Finally, to rank the indicators according to both the score from the literature, and aspects of data quality, a combined score, $\overline{Z_i}$, was calculated as:

$$\overline{Z_i} = \frac{\sum_{i=1}^{n} w_k * Z_i}{3}$$

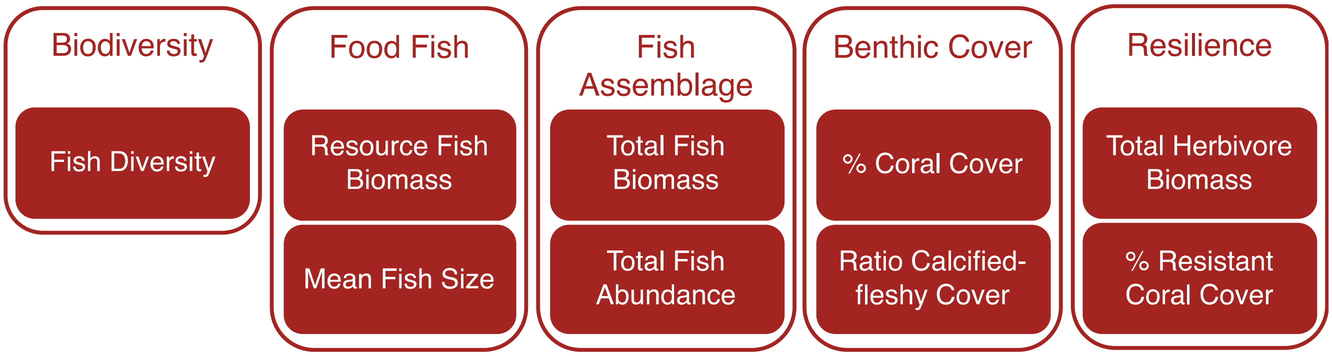
where Z_i is each of the 3 scores, and w_k is the weight for each score. The literature score was given the highest weight (= 1) and each of the data scores was given a weight of 0.25, and the indicators were ranked by their combined score within each category. The top two indicators in each category were selected as final indicators; if these two indicators were highly correlated, then only one was chosen.



Process for selecting final indicator set. Candidate ecological indicators were ranked using criteria based on the relevance and suitability of each indicator as interpreted from the peer-reviewed literature. This literature-based score was given the highest weight for evaluating candidate indicators. The coefficient of variation and effect size of each candidate indicator was also scored to evaluate the usability of each indicator within the HIMARC database. Each of these scores was weighted (*w*) and then averaged to get a combined score Z for each of 28 candidate indicators. Candidate indicators were ranked relative to the other candidate indicators within each of six key categories for measuring reef ecosystem state (i.e., biodiversity, fish assemblage, food fish, benthic cover, resilience, and herbivory), correlations were assessed, and the final set was chosen (Appendix 2).

Among candidate indicators (Appendix 2), mean fish size and fish species richness had the lowest $CV_{n=30}$ scores and, therefore, were ranked the highest. Effect size also varied among indicators, with coral cover, resistant coral cover, and turf algal cover having the largest effect size. Finally, a suite of fish biomass related indicators were highly correlated (rho > 0.7), including total fish biomass, total fish biomass minus sharks and jacks, resource fish biomass, herbivore biomass, parrotfish greater 25cm, and prime spawner biomass. Additionally, coral cover was correlated with coral:macroalgae ratio and with cover of resistant coral species. All scores and final ranking are in Appendix 2.

In summary, the top two indicators from each category were selected for the final set:



Final indicator set. Five core aspects of nearshore marine resources in Hawai‘i were identified. For each, 1-2 indicators (in red boxes) were selected as metrics to quantify the reef condition and track trends in marine resources.

Fish Diversity – A metric of the amount of fish species represented, measured as Shannon’s Diversity Index, which is combines richness (the number of species present) and evenness (the relative abundance of species present).

Resource Fish Biomass – The biomass of fishes that are targeted in local fisheries, which represents the overall stock status of reef associated fishes.

Mean Fish Size – The mean size of fishes that are targeted in local fisheries, providing an indicator of exploitation impacts.

Total Fish Biomass – The biomass of all fishes combined. Total fish biomass is an indicator of the status of the fish assemblage overall and is an integrated metric of size and abundance.

Total Fish Abundance – The numerical density of all fishes combined.

% Coral Cover – The proportion of bottom cover that is composed of corals. Corals are primary habitat forming species, and provide structure for the rest of the ecosystem.

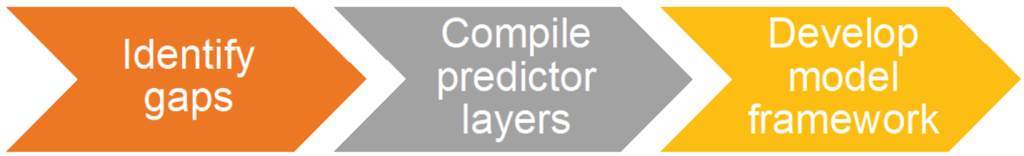
Ratio Calcified:Fleshy Cover – The ratio of the proportion of bottom cover composed of calcified organisms (corals and calcified algae) and fleshy organisms (turf algae and macroalgae), which is an indicator of the overall composition of the benthos.

Total Herbivore Biomass – the combined biomass of all herbivorous fishes. Herbivores consume algae, which can compete with corals for space, so they are important for maintaining a balanced system where corals can thrive.

% Resistant Coral Cover – The proportion of bottom cover that is comprised of coral species that are resistant to heat stress that causes coral bleaching. Coral species can react differently to stressors, and particular species were less likely to bleach during the 2014-15 event, so this metric serves as indicator of the amount of coral that can survive future heat stress events.

Estimate condition

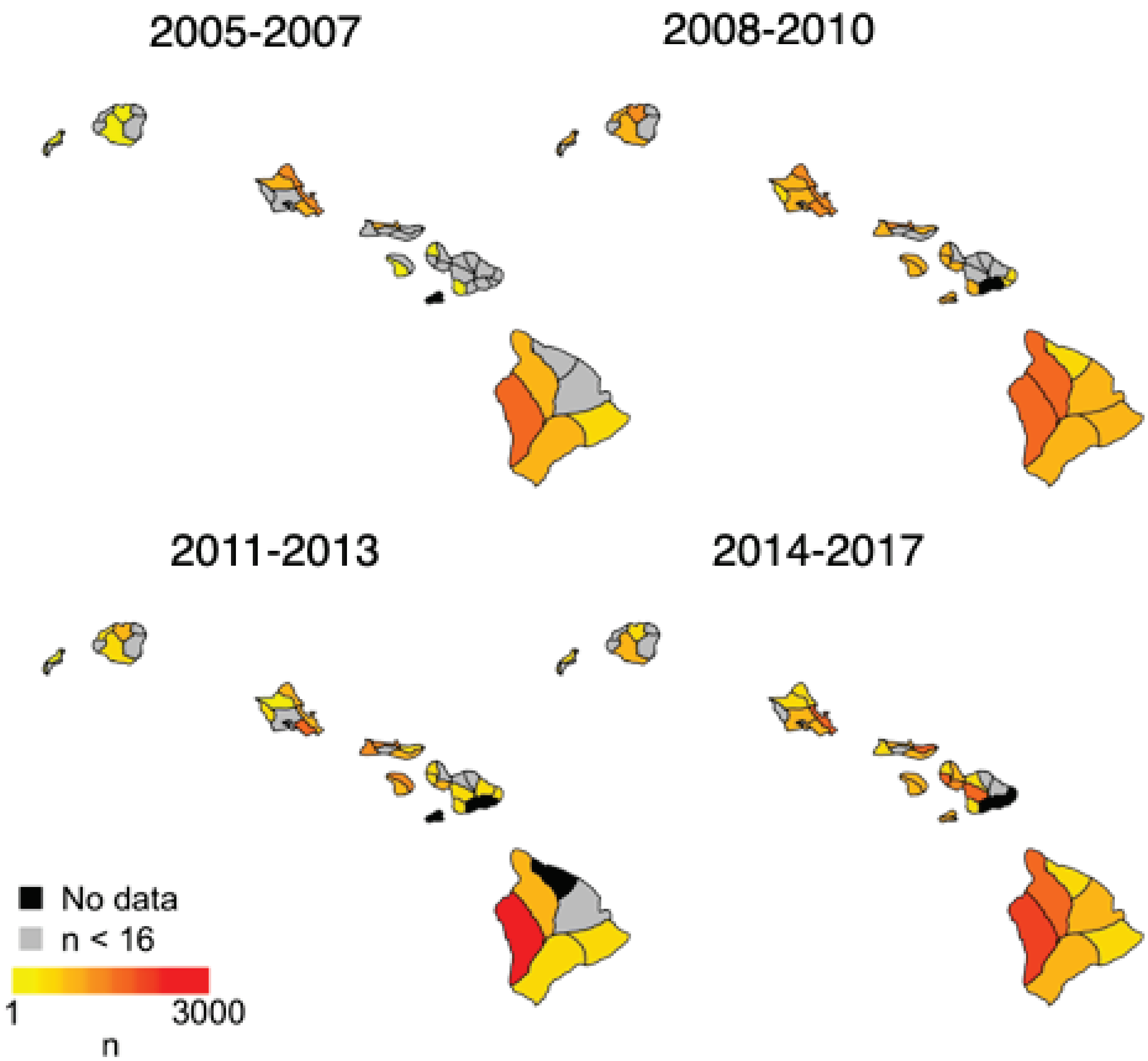
To achieve the best estimate of observed condition for each indicator, we created hierarchical Bayesian models that accounted for variation in space, time, data source, and were a function of human and environmental variables.



Identifying data gaps and their influence on estimates

Before estimation of indicators took place, steps were taken to explore factors that may be important due to gaps in the combined survey data. For example, spatial and temporal coverage varies between datasets and habitat types (e.g., depth, hard/soft bottom). To investigate gaps in data availability, the distribution of survey effort was evaluated across space (island, moku, and coastline scales), time (multi-year bins), and habitats (coral dominated, other hard bottom, and soft bottom).

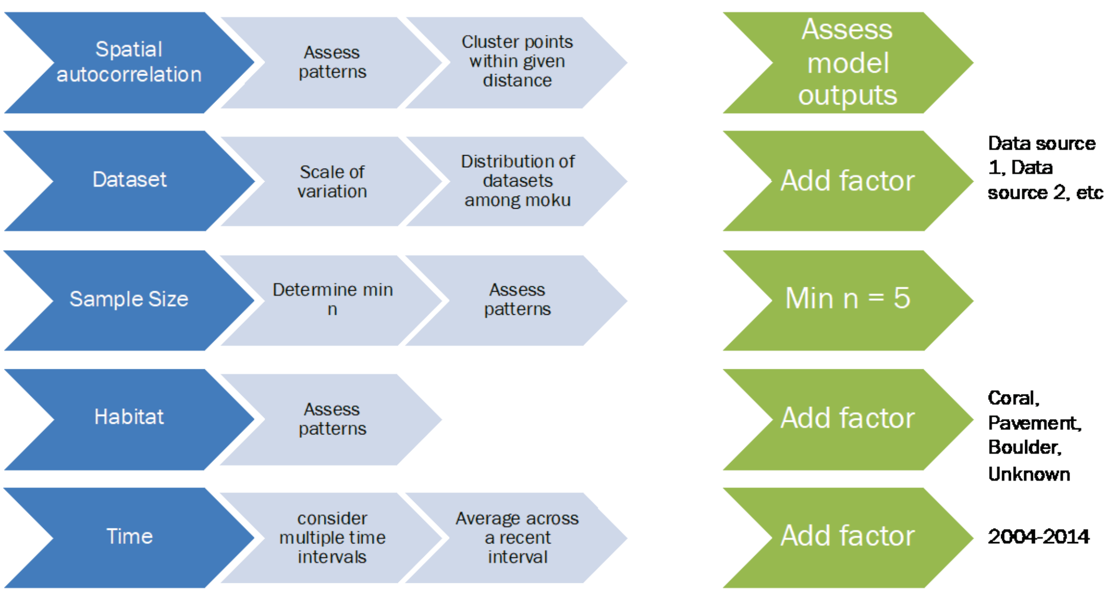
A closer look at the variation in indicators across datasets and moku showed that NOAA covers the greatest number of moku and that, while most moku have data from multiple datasets, some moku only have data from one dataset. The moku with the lowest survey coverage are on the southern coast on Maui and on the northeast and northwest corners of Kauaʻi. The distribution of survey intensity across moku was similar for fish and benthic surveys. When the distribution of surveys across moku is considered within subsets of the larger time series, more spatial gaps are apparent within the data. For example, Kahoʻolawe was surveyed only between 2008 and 2010, while surveys along the West Hawaiʻi coast were conducted during all three-year survey windows considered.



Data availability per moku given 4 distinct time windows. Data on the benthic and reef fish communities in nearshore waters around the State of Hawaiʻi are collected by a variety of organizations through underwater visual surveys. The availability of survey data reflects the combined capacity of these management organizations which varies through space and time. Moku are colored black when no data is available within that moku's coastline during a given 3-year time window. Moku are colored gray when less than 16 surveys are available. A color scale is used to depict moku when more than 16 surveys are available with yellow representing a lower number of available survey data and red representing a high number of available survey data.

In consultation with HIMARC stakeholders, a decision was made to base our modeling on data collected between 2004 and 2014. The motivation for this decision was to capture the condition of Hawaiian reefs prior to the 2014-2015 marine heatwave that caused widespread coral bleaching and subsequent mortality. Thus, the products generated here provide insight into the condition of reefs before this pulse event and will allow us to make meaningful inferences of how that event shaped Hawai‘i's reefs in future analyses of change over time. In doing so, it forestalls a ‘sliding baseline', where already-degraded reefs become normative. Importantly, the 2004-2014 period includes ~8000 observations that, together, form a spatially comprehensive and representative set.

Further, we explored how spatial autocorrelation, the distribution of datasets among moku, sample sizes within moku, habitat, and variation over time may influence the model outputs. As a result of this data exploration, habitat, dataset, year, and moku were included in the model as hierarchical effects. We also removed any moku that had less than 5 observations (Kahikinui, Kaupō, Mana), and tested for evidence that spatial autocorrelation had an effect on the modeled results.



Steps taken in final modeling. To assess patterns and the distribution of available survey data, five components of the available data were considered (blue text arrows). The patterns, variation, and distribution of available data across these components was assessed (gray text arrows). This data investigation process resulted in protocols to address these potential sources of bias (green text arrows).

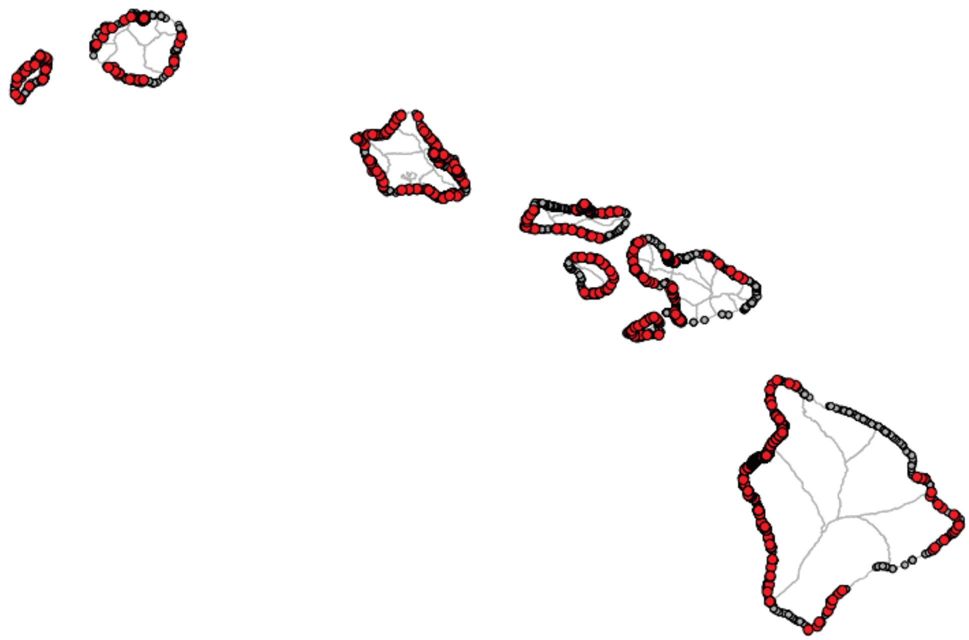
Compiling predictor layers

To effectively estimate indicators, we identified sets of predictors related to local human influence, including 1) land-based pollution and 2) fishing, and sets of predictors that influence indicators more broadly, including 3) physical oceanography, 4) habitat, and 5) spatial and temporal factors.

To be used in our modeling framework, predictors in each set had to be spatially comprehensive layers. For land-based pollution, fishing, and physical oceanography predictors, we relied on previously completed work by the Ocean Tipping Points Project (oceantippingpoints.org/Hawaii). Ocean Tipping Points environmental layers were based on methodological approach and results presented in Gove et al. (2013) and include sea surface temperature, chlorophyll-a, irradiance, and wave forcing and climatological metrics thereof (e.g., max, min, mean); Ocean Tipping Points human drivers include different types of fishing, sediment, nutrients from on-site waste disposal systems, habitat modification, and invasive species (Lecky 2016, Wedding et al. 2018). For habitat layers, we relied on habitat maps produced by NOAA's Biogeography Branch (Battista et al. 2007).

Further work was necessary in order to compile data on depth and rugosity, as these were not previously available in a comprehensive way for the main Hawaiian Islands. Depth information was missing from *in situ* observations for 20% of the data, and rugosity was not collected by most programs or in a comparable way by those that do collect such information.

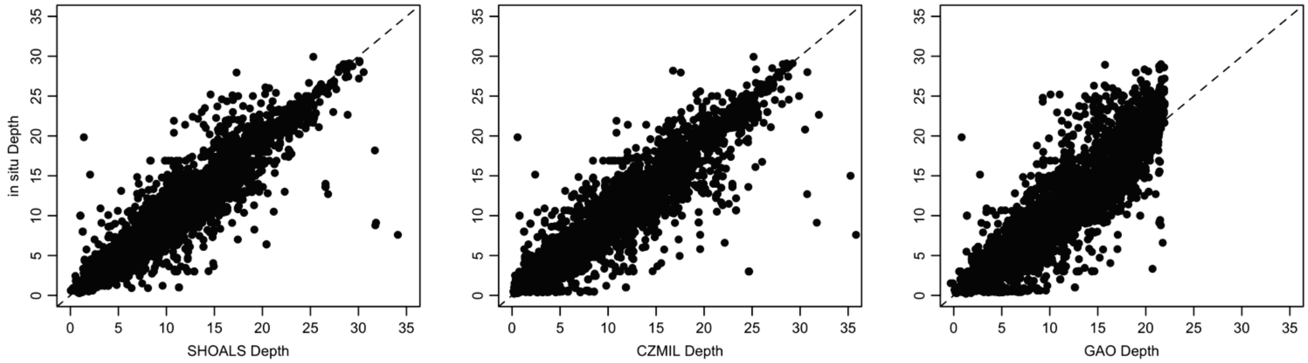
Remotely-sensed bathymetric data is reliable for depth and allows consistent measures of rugosity. In prior studies, we relied on bathymetric data from 1999-2001 aerial LiDAR surveys conducted by the Army Corps of Engineers (SHOALS); however, these data set has significant gaps that precluded statewide estimates of indicators. Thus, we undertook an effort to combine those data with two other data sources: aerial LiDAR surveys conducted by the Army Corps in 2013 (CZMIL), and imaging spectroscopy-derived depth data provided by Arizona State University's Global Airborne Observatory (GAO, Asner et al. 2020).



Surveys with missing depth data. The locations of all underwater visual surveys are depicted with dots across the State of Hawai‘i. Survey locations for surveys that are not associated with an *in situ* depth measurement are colored red.

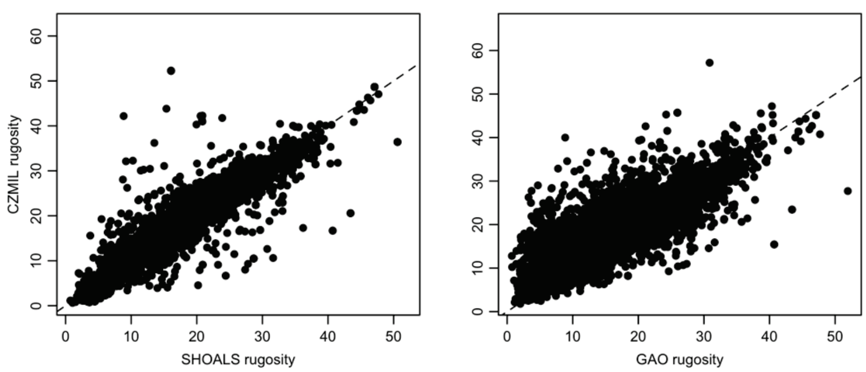
SHOALS and CZMIL data were processed from point cloud data to a depth raster at 5 km and 2 km, respectively. GAO depth data was provided at a resolution of 2 km. From these, topographic complexity (slope of slope) was derived from each on a 3x3 pixel neighborhood at the native resolution. The predictor metrics for depth and complexity used in modeling were based on the mean value within a 60 m radius of each pixel.

To derive a consistent depth metric from these three remotely-sensed data sets, we used *in situ* depth (i.e., depth recorded by a diver during the survey) as the response variable and all three of the remotely sensed bathymetry datasets as predictors. Using a Bayesian linear model with uninformative Normal priors on the slopes and constraining the intercept to zero, we created a predicted depth that was a weighted mean of the three bathymetry datasets. This model was used to estimate depth at every survey point and to create a spatially continuous, state-wide depth layer.



Correlations among *in situ* depth and bathymetry datasets. *In situ* depth measurements made by survey teams are graphed on the y axis for each graph, and the x axes for each graph depicts available depth data from a remotely sensed bathymetry dataset. The SHOALS depth data (left graph) is bathymetric data from 1999-2001 LiDAR surveys conducted by the Army Corps of Engineers. The CZMIL depth data (center graph) is bathymetric data from 2013 LiDAR surveys conducted by the Army Corps of Engineers. The GAO depth data (right graph) is imaging spectroscopy data from 2019 provided by Arizona State University's Global Airborne Observatory. For each graph, a 1:1 line is included (dashed graph line).

For rugosity, we followed a similar method, but could not rely on an *in situ* source as our response variable. Instead, we chose to use the CZMIL 2013 as the response variable and the SHOALS and GAO data sources as predictors. This model was used to estimate rugosity at every survey point and to create a spatially continuous, state-wide depth layer.



Correlations among rugosity from bathymetry datasets. Rugosity (slope of slope) from CZMIL depth data (center graph) is bathymetric data from 2013 LiDAR surveys conducted by the Army Corps of Engineers is on the y-axis. SHOALS depth data (left graph) is rugosity bathymetric data from 1999-2001 LiDAR surveys conducted by the Army Corps of Engineers. Rugosity from the GAO depth data (right graph) is imaging spectroscopy data from 2019 provided by Arizona State University's Global Airborne Observatory. For each graph, a 1:1 line is included (dashed graph line).

Predictors were chosen from a set of 109 total variables consisting of multiple metrics for several sets of predictors (e.g., mean, max, standard deviation). We grouped all predictors into 1) land-based pollution, 2) fishing, 3) physical oceanography, 4) habitat, and 5) spatial-temporal factors. We then investigated correlations between metrics within each group. Where variables were correlated above rho=0.7 we chose one variable to retain in the model based on whether it represented a distinct process compared to the other, which had a lower correlation to remaining variables, and which represented our best hypothesis for an effect on indicators. Our final models were based on a set of 27 predictors:

Land-Based Pollution

Urban runoff	Trash, household chemicals, oil from roads, and other forms of urban runoff were modeled as a proxy by calculating the area of impervious surfaces from the NOAA Coastal Change Analysis Program (CCAP) high resolution land use land cover per watershed and extending those values offshore.	Lecky 2016
Golf course runoff	Pesticides and fertilizers from golf courses were modeled as a proxy using subsets from CCAP 'open developed space' and validated with Google Earth and ESRI Imagery to calculate golf course area per watershed and dispersing those values offshore.	Lecky 2016
Agricultural runoff	Pesticides and fertilizers from agricultural runoff were modeled as a proxy by calculating the area of agricultural land from CCAP per watershed and extending those values offshore.	Lecky 2016
Habitat modification	Direct alteration, removal, and destruction of habitat including coastal engineering (e.g., seawalls, piers), dredging, and offshore aquaculture were compiled and represented as presence and absence.	Lecky 2016, Wedding et al. 2018
Sedimentation	Modeled with the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) sediment delivery ratio model to estimate the annual average delivery of sediment offshore.	Lecky 2016, Wedding et al. 2018
On-site waste disposal effluent	Estimated nutrient flux from on-site waste disposal systems (cesspools, septic tanks) from estimated flux by land parcel from the Hawaii Department of Health and proximity to individual systems.	Lecky 2016, Wedding et al. 2018

Fishing

Non-commercial boat-based net	Island-scale annual average non-commercial boat-based reef fisheries catch (kg/ha) from all nets and spears were calculated from the Marine Recreational Information Program data. Values were mapped offshore by modeling the distance to harbors and boat launches and human population within 30 km, and MPA regulations.	McCoy et al. 2018, Lecky 2016, Wedding et al. 2018
Non-commercial boat-based spear		
Non-commercial shore-based spear	Island-scale annual average non-commercial shore-based reef fisheries catch (kg/ha) from all spear and line were	

Non-commercial shore-based line	calculated from MRIP data. Values were mapped offshore by modeling shoreline accessibility using TIGER roads and USGS DEM slope and MPA regulations.	Lecky 2016, Wedding et al. 2018
Aquarium Collection	Average annual reported commercial aquarium catch (#/ha) from 2003-2015 by reporting block from the Hawai'i Division of Aquatic Resources.	Lecky 2016
Commercial line **Commercial spear**	Average annual commercial catch of reef fish species (kg/ha) with line and spear gear types by reporting block from 2003-2013 from Hawai'i Division of Aquatic Resources.	Lecky 2016, Wedding et al. 2018

Physical Oceanography

Temperature standard deviation **Temperature long-term mean**	Mean and standard deviation of sea surface temperature from weekly 5 km NOAA blended satellite data from 2000-2013.	Gove et al. 2013, Wedding et al. 2018
Irradiance long-term mean	Mean solar radiation at the ocean surface from 4 km MODIS, 8-day composites from 2002-2013.	Gove et al. 2013, Wedding et al. 2018
Wave anomaly maximum **Wave anomaly frequency**	Wave power anomaly maximum and frequency from 0.5-1 km hourly data from the Simulating Waves Nearshore (SWAN) model from 2000-2013.	Gove et al. 2013, Wedding et al. 2018
Chl-*a* anomaly maximum **Chl-*a* anomaly freqency** **Chl-*a* long term mean**	Cholorphyll-*a* long term mean, and anomaly frequency and maximum from 4 km MODIS, 8-day composites from 2002-2013.	Gove et al. 2013, Wedding et al. 2018

Habitat

Depth	Blended depth from in situ surveys, 1999-2001 LiDAR surveys conducted by the Army Corps of Engineers (SHOALS), LiDAR surveys conducted by the Army Corps in 2013 (CZMIL), and imaging spectroscopy data provided by Arizona State University's Global Airborne Observatory (Asner et al. 2020).	
Complexity	Blended slope of slope from 1999-2001 LiDAR surveys conducted by the Army Corps of Engineers (SHOALS), LiDAR surveys conducted by the Army Corps in 2013 (CZMIL), and imaging spectroscopy data provided by Arizona State University's Global Airborne Observatory (Asner et al. 2020).	
Habitat type	Coral, pavement, boulder, and other habitat based on maps produced by NOAA's Biogeography Branch	Battista et al. 2007

Modeling framework

We modeled each indicator with a Bayesian hierarchical model to incorporate uncertainty at multiple spatial and temporal scales. Underwater survey data is inherently variable, particularly for fish metrics, and the hierarchical modeling structure allows us to find meaningful relationships at larger spatial scales, despite that inherent variability. This approach also accounts for 'unbalanced' data – where data are not evenly spread across depth, moku, or other important features – and for variability due to differences between monitoring programs, time, and space. Finally, this approach allows us to model each indicator according to its natural statistical distribution. All models were implemented in the *R* statistical environment, and codes were developed and documented to facilitate similar future analyses as the HIMARC database continues to be updated.

Model Details

We constructed Bayesian hierarchical models customized for each indicator variable: total fish biomass, herbivore biomass, and resource fish biomass were modeled with a Gamma distribution; coral cover was modeled with a Beta distribution; mean fish size, ratio of calcified to fleshy, total fish abundance, and fish diversity were modeled with a Normal distribution.

We parameterized the Gamma in terms of the mean (μ) using:

$$y_{imyd} \sim Gamma(\kappa, \kappa \cdot e^{\mu_{imyd}}),$$
$$\kappa \sim U(0{,}100).$$

We parameterized the Beta in terms of the mean (μ) using:

$$y_{imyd} \sim Beta\left(r \cdot \mu_{imyd}, r \cdot \left(1 - \mu_{imyd}\right)\right),$$
$$r \sim Gamma(0.1{,}0.1).$$

We parameterized the Normal in terms of the mean (μ) using:

$$y_{imyd} \sim Normal\left(\mu_{imyd}, \tau_y\right),$$
$$\tau_y \sim Gamma(0.1{,}0.1),$$
$$\sigma_y = 1/\tau_y^{-2}.$$

We then modeled the mean as linear function of multiple predictors (β) related to habitat, environmental conditions, fishing impacts, and land-based impacts. All continuous predictors were standardized to a zero mean and unit variance to improve model convergence across predictors with different units. We also included hierarchical effects of year (y) to account for variation over time, of moku (*m*) to account for spatial variation, and of dataset (*d*) to account for effects of combining data from multiple methods and survey designs, as:

$$\mu_{imyd} = \varepsilon_y + \varepsilon_d + \varepsilon_m + \vec{\beta}\vec{\mathbf{X}},$$
$$\vec{\beta} \sim Normal(0,100).$$

In order to ensure identifiability of the hierarchical effects, we implemented a 'sum-to-zero-constraint' as described by Ogle & Barber (2020). In summary, when hierarchical effects variance is large relative to the sample variance this can create 'nearly' non-identifiable parameters as result of implementation of Markov chain Monte Carlo (MCMC) methods that result in correlated posteriors. To address this, a constraint can be implemented to constrain the average of the hierarchical effect to zero, such that for example the hierarchical effect of year as:

$$\varepsilon_y \sim Normal(0, \sigma^2_{\varepsilon_y}) \text{ for } y = 1,2,\ldots,Y\text{-}1$$

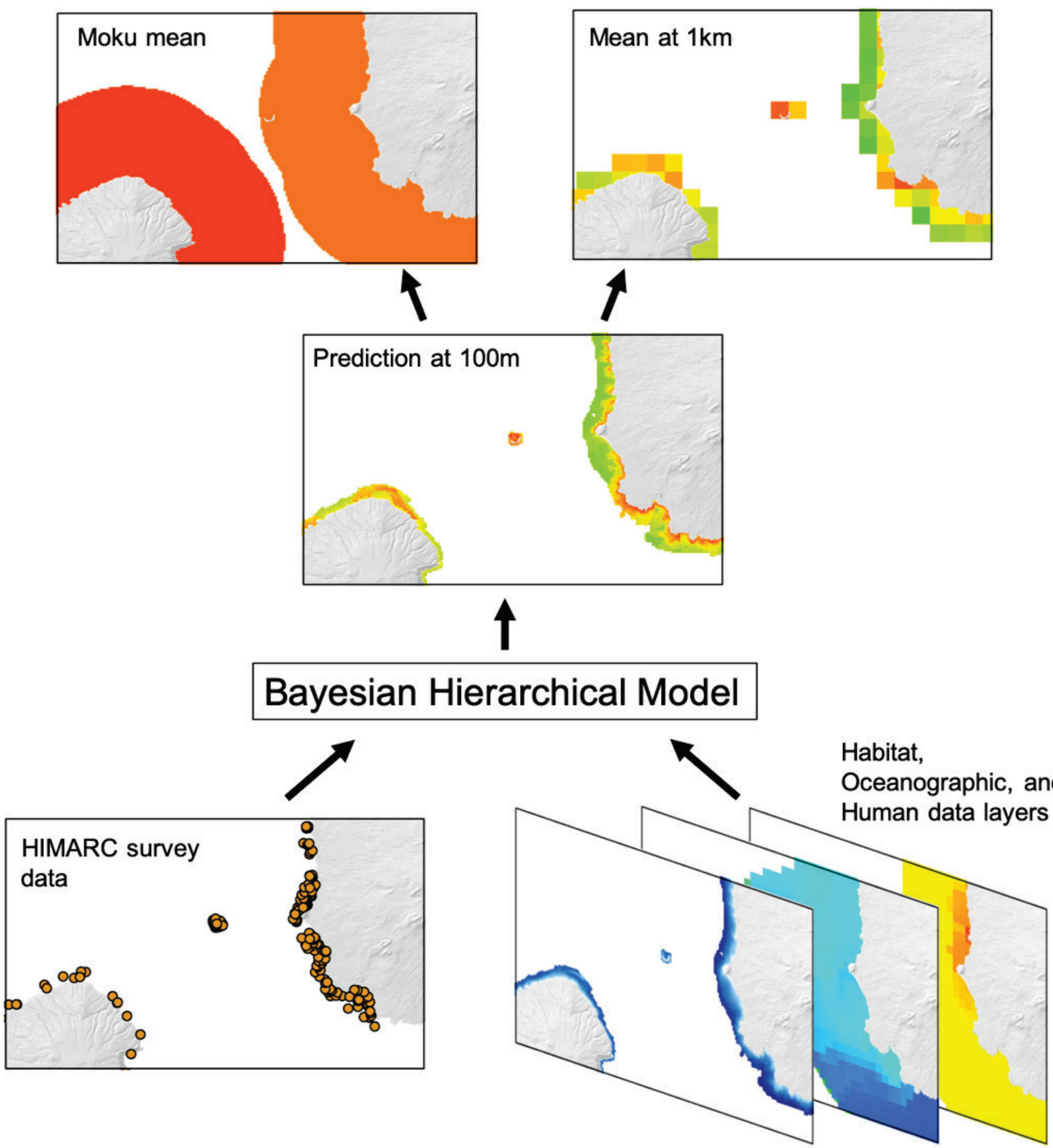
$$\varepsilon_Y = -\sum_{y=1}^{Y=1} \varepsilon_y$$

The models were fit with JAGS via the *rjags* package in R (Plummer 2016) with 5000 iterations, including a burn-in of 2,000 iterations, with posterior estimates based on the remaining 3,000 iterations. Model convergence was assessed by running 3 chains and calculating Gelman-Rubin statistics (Gelman & Rubin 1992). Model fits were assessed with posterior predictive checks and Bayesian R^2, and plotting predicted versus observed values for all observations.

Spatial presentation of model results

Model inputs were based on geographic coordinates where survey data were located. Because the combined surveys were designed for many different purposes, the resulting data are not evenly distributed across space and, therefore, are not representative of habitats across the study domain. To produce appropriately-weighted indicator estimates, we post-stratified the predictions. That is, we predicted the indicators based on drivers at a resolution of 100 meters and then spatially-summarized these indicators to a larger scale: either 1-km or the moku scale. This gives every prediction in the 100-meter grid equal weight in the 1-km or moku estimates (Appendix 3).

To produce predicted maps, each of the 27 predictor surfaces were preprocessed to conform to consistent 100 m spatial resolution, grid alignment, extent, and projected coordinate system (NAD 83, UTM zone 4). Predictor layers with native resolutions coarser than 100 m were resampled with the nearest neighbor technique in order to avoid introducing artificial data values and maintain the spatial patterns of the native resolution. Composite depth and complexity layers were produced at 100 m resolution by aggregating the native resolution rasters of 60 m radius mean values to 100 m resolution by calculating the mean of pixels within 100 m x 100 m blocks. For the composite depth surface, raster cell values were filled by priority rank order of data sources, with CZMIL having highest priority, followed by SHOALS, and then GAO only in areas where no LiDAR exists. For complexity, we used a similar priority based method with CZMIL first but then transformed/weighted values for SHOALS and GAO using a linear predictive relationship between each data source and CZMIL data.



Process for summarizing model results. A Bayesian hierarchical model was used to quantify relationships between indicators and predictors for each survey location while accounting for the spatial and temporal structure of the survey data. With this model, indicator condition was predicted for all nearshore locations (100m grid. These best estimates of observed reef ecosystem status were then summarized at the 1km and moku scale.

Sources of uncertainty and spatial variation

Indicator predictions are made at the 100-m resolution and have several sources of uncertainty:

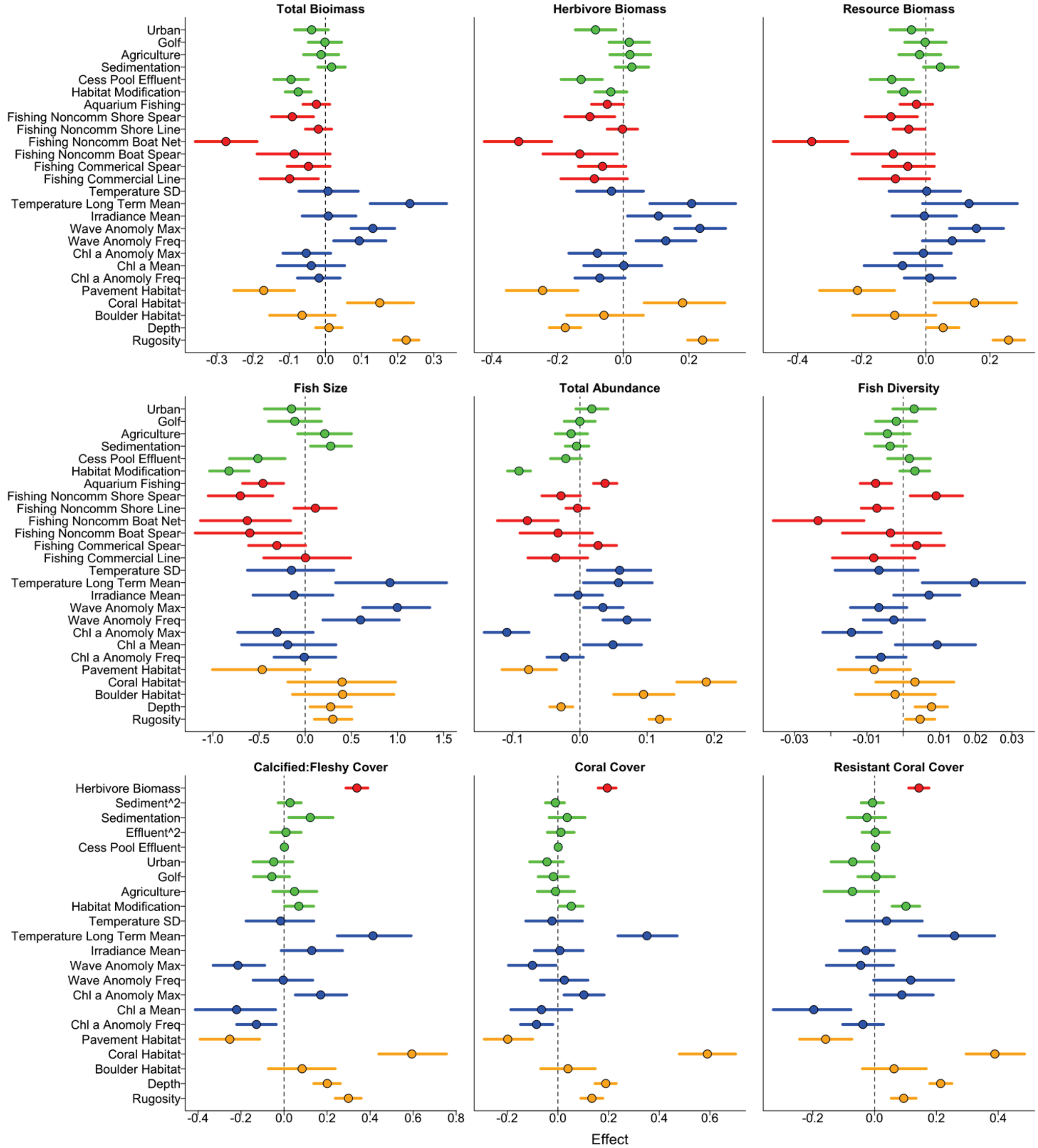
(i) Uncertainty in Effect Size: this is the uncertainty in our estimate of the effect of each driver variable on the indicator given the model; this uncertainty is represented as a 95% Bayesian interval around the median value in the plot of effects of each predictor on each indicator. Maps in the appendix are based on median effect size.

(ii) Uncertainty in Drivers: the model assumes that the driver variables are measured exactly – that is, that there is no error in the observed value in either the actual survey data or in the driver data extrapolated to the 100m map resolution. The model also assumes that the driver value at the 100m resolution applies uniformly at that scale. This introduces additional uncertainty in both the effect sizes and the model predictions.

(iii) Unexplained Variance: all indicator models include driver variables and hierarchical spatial variation at the moku scale. However, these models explain only a fraction of the variability in the observed data. The remaining, unexplained variance is attributable to uncertainty in drivers, unobserved driver variables that were not included in the model, and the fundamental stochasticity in the observation process. For example, even at the same site on the same day, two survey teams will encounter different numbers and sizes of fish due to the limitations of the sampling process.

Indicator maps were created from predictions at 100m resolution and then are spatially summarized to the 1-km and/or moku scales (Appendix 3). These spatially-summarized predictions are averages over space; therefore, the mean indicator values represented in the indicator maps should be interpreted with care, acknowledging both the model uncertainty and spatial variability that underlie them.

Indicator condition



Effects for each predictor on each indicator, from Bayesian hierarchical models that accounted for spatial and temporal structure in the data. Effects (y-axis) are colored to correspond with land-based pollution variables (green), fishing variables (red), oceanographic variables (blue), and habitat variables (orange). Points are median of posterior estimates and horizontal lines are 95% Bayesian intervals; vertical dashed line represents zero effect. Intervals that do not cross the zero line represent a negative (to the left of zero line) or positive (to the right of zero line) effect on indicator condition.

We found some consistent patterns across key predictors:

- **Non-commercial boat-based net fishing** had a consistent and large negative effect on all fish indicators. **Non-commercial boat and shore-based spear fishing** also both had a consistent negative effect on all fish indicators except for fish diversity.

- **Herbivore biomass** had a consistent and large positive effect on benthic variables.

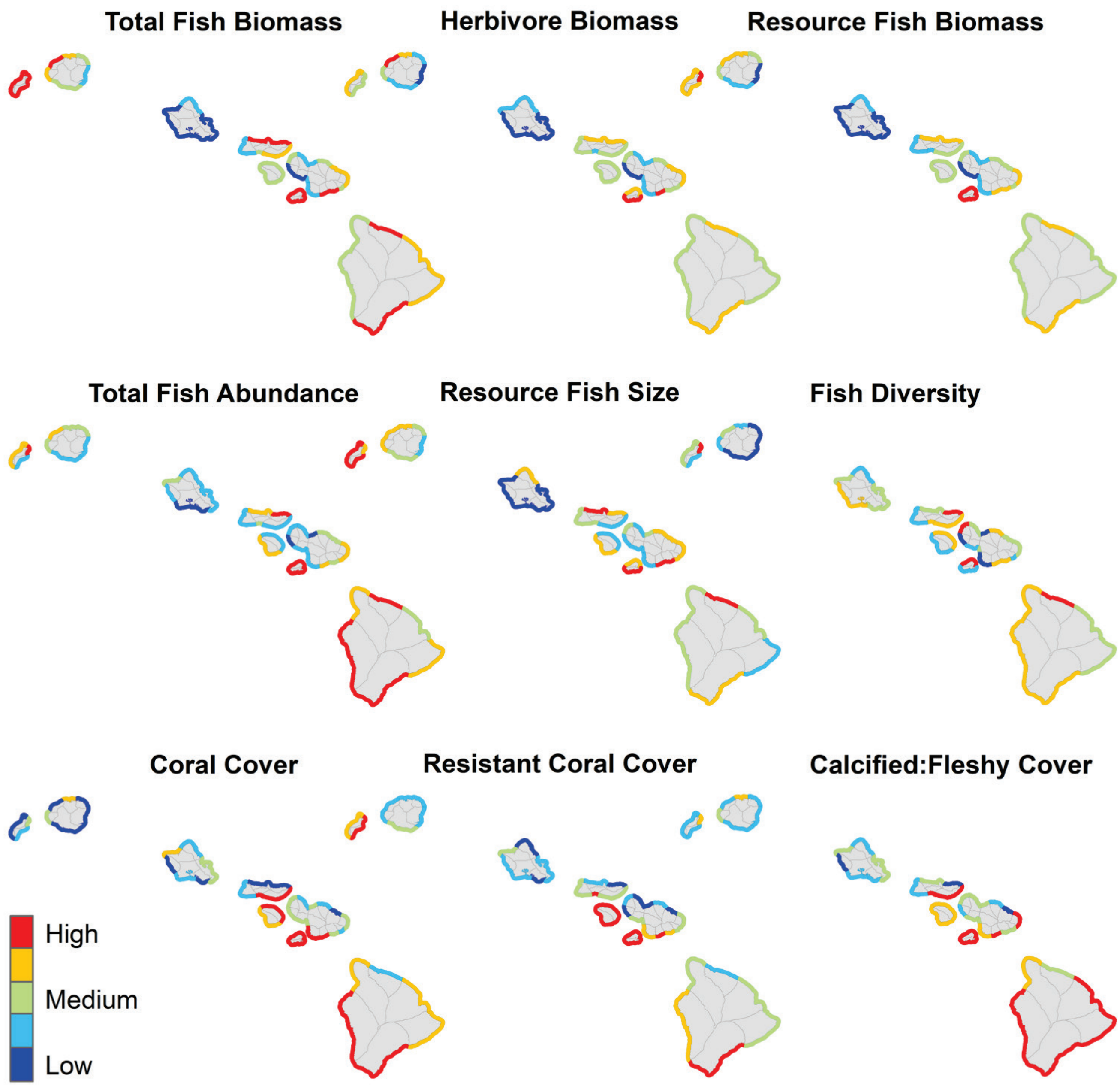
- Negative effects of **land-based pollution** were evident for fish indicators, and less conclusive for benthic indicators. Cess pool effluent and habitat modification negatively affected fishes.

- Oceanographic and habitat variables were important across all indicators, underscoring the necessity of accounting for these effects when interpreting patterns of human impacts in Hawaiʻi.

When the indicator models are mapped at the moku scale, spatial patterns across the ecological indicators become evident:

- Some moku were consistently high across all indicators, such as Kahoʻolawe and Puna Hawaiʻi.
- Others had high values for fish related metrics, but varied in benthic cover, such as Niʻihau and Koʻolau Molokaʻi.
- Several moku were low across all indicators including Kona and Ewa Oʻahu and Lahaina Maui.
- Focusing on resilience indicators, Kona Kahoʻolawe, Koʻolau Kahoʻolawe, Hana Maui, and Hāmākua Hawaiʻi ranked the highest, while all of the lowest were all on Oʻahu including Waiʻanae, Kona, Hāmākuapoko and Ewa.

Detailed maps of each indicator are provided in Appendix 3.

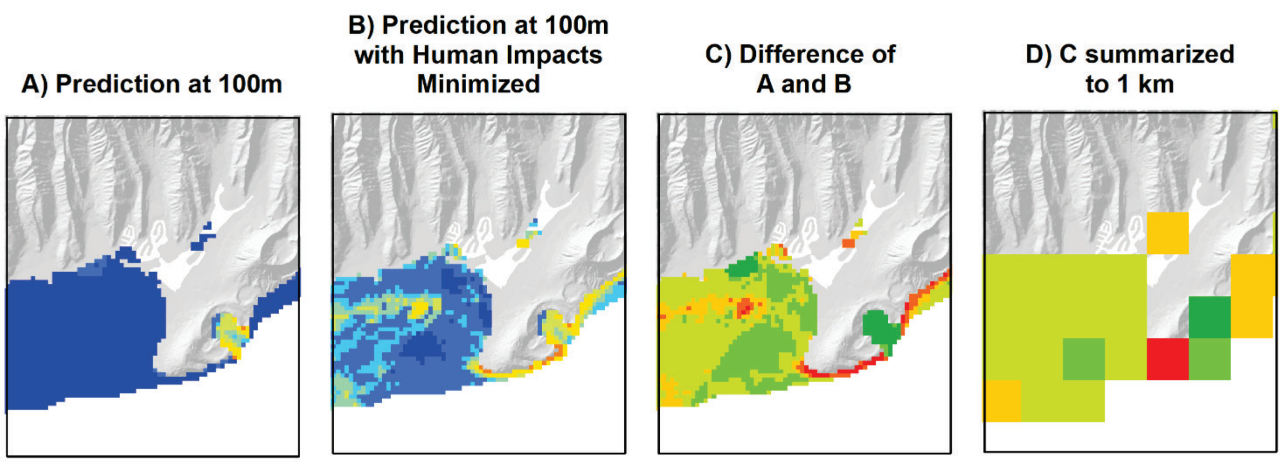


Moku-scale average condition for each of nine indicators. These values were calculated using all available survey data and estimating the condition across the full moku based on spatially-explicit values of predictor variables. Condition is presented using a color scale from high values (red) to low values (blue). Values for each indicator are relative to the values of that indicator across the other moku within the State of Hawai‘i.

Modeling recovery potential

Indicators are most valuable to managers when they are contextualized in terms of potential management actions. Here, we develop a model of recovery potential to identify areas that are likely to be responsive to management action, given the environmental conditions at the site. For example, we might expect coral cover to be lower in areas with large wave events compared to more sheltered environments, even in the absence of human impacts. We used this thinking to develop maps of recovery potential – the difference between the current condition of a site and its *potential* condition when human impacts are reduced (Appendix 4).

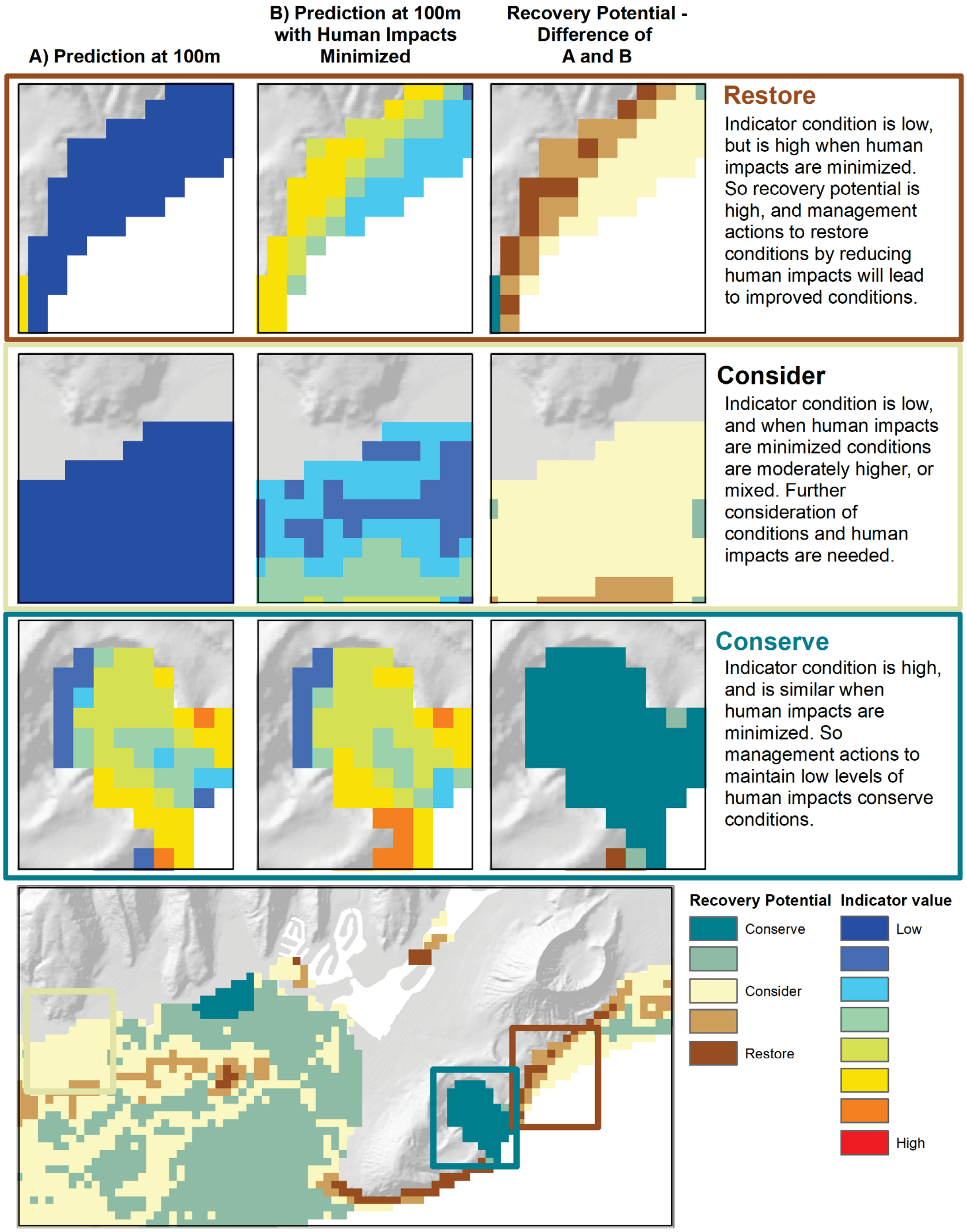
Recovery potential was estimated by comparing maps of observed indicator condition (Appendix 3) to maps where human impacts were minimized. That is, by accounting for variation in factors over which humans have little or no control (e.g., oceanographic and habitat variables), we isolate the effect of human impacts and identify areas that will be most responsive to management actions.



Methods for mapping recovery potential. For each indicator, spatially explicit estimates of observed condition were modeled at 100 m and summarized to 1km. Predictions from Bayesian hierarchical models based on survey observations and oceanographic variables, habitat characteristics, and human impacts were generated at 100m. Human input variables were then minimized and another prediction as made at 100m. These two maps were subtracted to produce a map of recovery potential, which was then summarized at 1 km.

Interpreting recovery potential

Recovery potential gives our best estimate of a location's responsiveness to management action. These management actions can be divided into 3 categories: **Restore**, **Consider**, and **Conserve**.



Interpreting recovery potential. We have categorized recovery potential along a gradient that corresponds to three management implications: restore, consider, conserve.

Areas indicated **Restore** are regions most likely to respond to a decrease in human pressures.

Areas indicated **Conserve** are regions with low recovery potential and, often, high indicator values; i.e., less accessible regions where high indicator values may require protection rather than restoration.

Finally, areas indicated **Consider** require additional analysis: these regions may contain a mix of high and low recovery potential or uncertainty in the degree of recovery possible.

Management prioritization, therefore, will need to consider both indicator condition (Appendix 3) and the potential for recovery (Appendix 4).

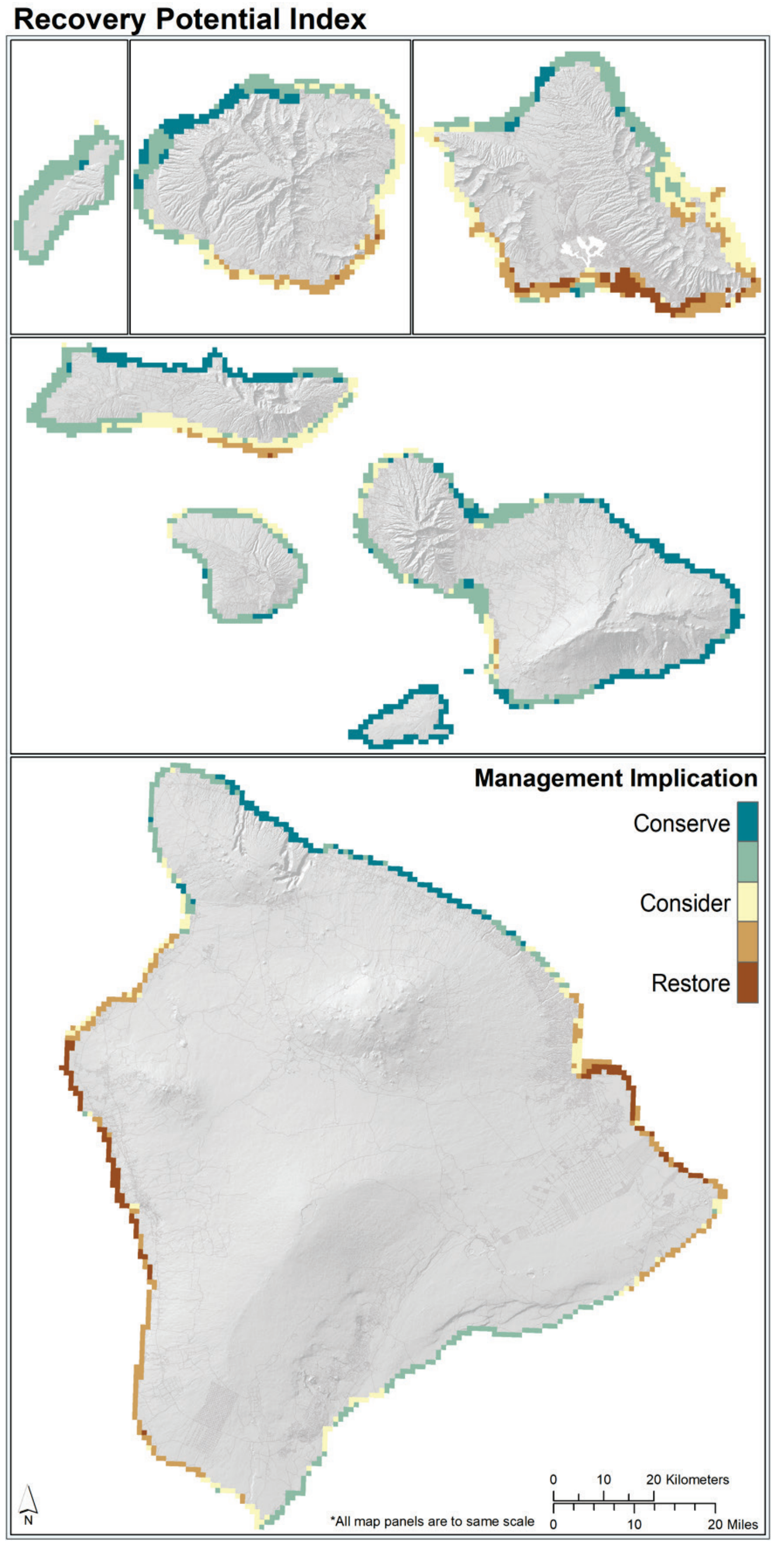
Recovery potential – results

- Reducing human impacts in South O‘ahu, South Kaua‘i, South Moloka‘i, and East and West Hawai‘i could result in improvements across all indicators.

- Human impacts did not reduce conditions on remote, north facing shorelines, implying that effective management in these areas will conserve conditions.

- East Kaua‘i, Wai‘anae, Ko‘olaupoko, South Moloka‘i, West Maui, and Kihei Maui had mixed effects of human impacts, so further consideration of individual indicators will determine what actions will lead to effective management.

Maps of Recovery Potential for each indicator independently are provided in Appendix 4.



A combined index of recovery potential for a 9 indicators is shown at the 1-km resolution across nearshore habitat in the State of Hawai‘i. Green corresponds to locations where the current condition is similar to the predicted condition if human impacts were decreased. High recovery potential (red) corresponds to locations where the current condition is substantially lower than the predicted condition if human impacts were decreased.

Applications to management

The maps presented provide the condition of ecological indicators for reefs around the State of Hawaiʻi prior to the 2014-2015 bleaching event. These results have direct management relevance for Hawaiʻi DLNR's Division of Aquatic Resources (DAR) as they implement the Sustainable Hawaiʻi Initiative marine goal of *"effectively managing 30% of Hawaiʻi's nearshore by 2030"*. This study was designed in collaboration with DAR staff and the HIMARC partners who conduct monitoring of nearshore marine resources in Hawaiʻi.

The products from this project have multiple applications for management, including 1) documenting nearshore marine resource conditions, 2) identifying areas most likely to benefit from management action, 3) creating specific and measurable resource recovery targets, and 4) evaluating outcomes after management actions are taken.

Documenting conditions

Critical to any decision-making process is evaluating current conditions to provide the basis for which decisions can be made. For nearshore marine resource management, this includes taking stock of what condition the ecosystem is in. This process has identified a set of nine indicators of ecosystem condition, which were then estimated across the State of Hawaiʻi at multiple spatial scales. These maps can be used by resource managers and communities to consider the ecosystem condition for a specific region of interest relative to other regions across the State. In addition, these estimates of observed, pre-bleaching ecosystem condition provide a baseline to which ongoing and future measurements of ecosystem condition can be compared.

Identifying areas most likely to benefit from management

There are many determinants of ecosystem condition, only some of which are connected with human impacts and can be influenced by local management action. The model developed here carefully accounts for spatial and temporal biases in the survey data, and the model directly incorporates the role of oceanographic variables and habitat characteristics on observed reef communities.

To identify locations with high recovery potential, human impacts were minimized to reflect potential management actions. This recovery potential metric controls for the natural, site-specific, limits imposed on each indicator by the oceanographic and habitat characteristics and provides spatially explicit insight into the expected change given a decrease in human impacts.

Together, maps of indicator condition and recovery potential can help managers and communities prioritize actions in any region of interest. In places where current conditions are high and recovery potential is low, management actions can be taken to **conserve** current conditions. In places where current conditions are diminished and, thus, recovery potential is high, management actions can be taken to **restore** indicator conditions. Specific management goals may be similar in both cases (e.g., limit overharvesting of fishes), but policy implementation would tailored by region.

As actions are taken, the ecological indicators developed here provide key metrics for measuring a range of ecological responses to management actions and evaluating the effectiveness of management. For example, we will want to see current conditions stay the same in places identified for conservation, and we will want to see current conditions improve in places identified for restoration.

Identifying specific and measurable targets

Recovery potential metrics from this study inform realistic expectations for ecological responses to management actions. With recovery potential predicted for each of nine ecological indicators, managers and community members can consider distinct components of the ecosystem when designing management actions and identifying target outcomes. The spatial resolution of our data products allows for these conversations and decisions to be made on local and regional scales.

Evaluating outcomes after management actions are taken

The process we followed to identify, select, and estimate baseline values for ecological indicators of nearshore marine resources in Hawaiʻi provides a clear path for evaluating ecological outcomes of management actions in the future. The ecological indicators presented here were selected for management interpretability and their capacity to capture ecosystem responses to management action. The indicator estimates of observed ecosystem condition provide a baseline against which ongoing and future measurements of ecosystem state can be compared. Our modeling framework, which provides a statistically sound way to account for spatial and temporal nuances of an integrated, statewide database, can be redeployed for future, updated condition estimates. Following this protocol for future estimates of observed condition ensures that evaluation of the ecological outcomes from management actions are not biased by potential differences in the distribution of survey sites across the original, ongoing, and future estimates of ecosystem status.

Next steps

Data integration moving forward

Continued improvement and institutionalization in dataset comparability through capacity building

The current QAQC process has greatly strengthened conversations with data providers and improved the quality of data. However, the process is time-intensive and requires dedicated, highly trained personnel. A key next step for the HIMARC collaboration is to leverage the process undertaken here to improve the QAQC capacity within partner organizations. Increased capacity for QAQC within data partner organizations would increase the value of these data within each organization and greatly reduce the time and cost of statewide data integration going forward.

Calibration update

The fish surveys used to estimate five of the indicators in this study comprise five distinct survey methods: 25m transects with a 4m belt, 25m transects with a 5m belt, 25m transects that use a size cut off to focus on smaller fishes within a 2m belt and larger fishes within a 4m belt, and a stationary point count. The differences in these reef fish survey methods used by partner organizations across the State of Hawaiʻi have species-specific biases in the density of fish observed. Cross-calibration between survey methods can control for some of these biases.

The calibration method used in this study was developed collaboratively with NOAA in 2013-2014 and uses the NOAA Biogeography Program belt transect surveys as the standard against which all other survey types are calibrated (Donovan et al. 2018). The calibration factors were developed using general linear models and Monte Carlo simulations (Nadon 2014). The resolution (i.e., species, family-functional group combo, or global) at which each species-specific calibration factor was calculated depends on available observations of the species between each pair of datasets, the frequency of non-observations, and the model fit.

In the process of this study, we have identified key gaps and biases in the current calibration process and recognize the importance of updating this method. The current calibration method is based on data integrated into the HIMARC database by 2014. The amount of data as well as the region-specific overlap of surveys using different methods has greatly increased in recent updates of the database. In addition to taking advantage of advances in computing capacity and statistical software, updating the calibration is critical to account for the updated suite of fish observation data available across spatial and temporal scales.

Ideally, calibration factors would be developed empirically by using all fish survey methods on the same reef at the same time across multiple locations. This would allow direct comparison fish counts and sizes across the methods. Alternatively, systematically grouping surveys by location and time window at varying scales depending on the number of paired observations between survey methods for each species can provide reliable, statistical estimation of calibration factors. Two key challenges in developing calibration factors are appropriately handling non-observations of species and accounting for uncertainty within the calibration factors.

Updating the calibration factors across fish survey methods is a high priority for HIMARC as it is a critical step in curating a statewide database reliant on data from multiple organizations to guide management decisions.

Memorandum of understanding for HIMARC partner organizations

Various HIMARC partner meetings and conversations have included discussions of best practices for sharing and working with available datasets. To date, a formal Memorandum of Understanding (MOU) that outlines the procedures for requesting HIMARC data, working with these data, and citing these data has not yet been developed. As interest in working with the HIMARC database continues to grow, data partners need to reach consensus on protocols for managing and responding to data requests, filling data requests, and documenting what research is using data from within HIMARC. HIMARC acknowledges development of an MOU as a critical next step to formalize protocols for internal and external requests for data.

Applications to management

Reef communities are complex ecosystems with various feedbacks, interactions, and nonlinearities. Further, ecological and social systems are tightly coupled, which involves even greater complexity.

We have worked to account for some complexity in the coupled social-ecological system within our Bayesian hierarchical modeling framework. However, there are critical extensions to this model framework that will improve management relevance and continue to leverage the massive dataset we have complied and continuing to update.

Furthering our understanding of human impacts on indicator condition

Our models considered multiple human impacts and their effects on indicator conditions. Yet, there remains unexplained variation in indicators that may be explained by further consideration of human impacts. In particular, we did not account for interactions, nonlinearities, or feedbacks. Interactions can explain how one the level of one predictor influences the effect of a second predictor. For example, an interaction between wave energy and land-based pollution may capture how wave energy may quickly disperse pollutants entering the reef, decreasing the effect of land-based pollution compared to a location with lower wave energy. Nonlinearities can explain how the effect of a predictor on an indicator changes at different levels of that predictor. For example, small amounts of sedimentation may have little effect on condition, but increasing sedimentation above a threshold may cause rapid deterioration in condition, leading to a ‘tipping point’. Feedbacks occur when the predictor variable is itself affected by the indicator. For example, benthic and fish variables are highly coupled – we found that herbivore biomass was a strong predictor of coral indicators and that coral habitat was a strong predictor of herbivore biomass. Feedbacks would allow these bi-directional effects into the model. Incorporating interactions, nonlinearities, and feedbacks are all extensions of our current modeling framework that would improve the predictive capacity of the model.

Overlaying climate change

Climate change is a fundamental threat to coral reefs, most immediately due to increasing frequency, duration, and magnitude of marine heat waves that cause coral bleaching and mortality. Reefs in the State of Hawai‘i experienced marine heatwaves in 2014-15 and again in 2019. Thus, it is critical for the patterns identified in this project to be overlaid with those impacts when making management decisions. One approach is to compare the 2004-2014 indicator maps developed here with the post-bleaching indicator conditions from 2015-2020. A second approach, is to overlay our maps of recovery potential with maps of vulnerability to climate change.

Management planning through scenarios

In this project, we uncovered substantial variation in recovery potential for nine indicators across coastlines in the State of Hawai‘i. Underlying this variation in recovery potential are the established relationships between specific human impacts and each indicator. These models can now be used to understand how a given impact, e.g., a specific fishing gear or modality, may be having an effect in a certain area. Similarly, the models could be used to examine the relative importance of different human impacts in a particular region, e.g., a comparison of fishing and land-based impacts. For example, given a region that has been identified as having a high recovery potential for reef fish biomass, we could investigate the separate impacts of restricting specific fishing gear types, or modifying land-based inputs, or increasing habitat complexity. Working in a targeted fashion to evaluate potential management scenarios, the HIMARC recovery potential model could be a key tool to inform planning scenarios by region and management action.

Evaluating outcomes after management actions are taken

As HIMARC continues to integrate new data from partner organizations, the database of statewide reef survey data can continue to inform management by quantifying the ecological outcomes of management actions. A next step is to evaluate the temporal variation and trends through time for each ecological indicator, and to compare these patterns between areas with and without management actions. This can serve as measure of effective management.

References

Adam TC, Burkepile DE, Ruttenberg BI, Paddack MJ (2015a) Herbivory and the resilience of Caribbean coral reefs: knowledge gaps and implications for management. Mar Ecol Prog Ser 520:1–20.

Adam TC, Kelley M, Ruttenberg BI, Burkepile DE (2015b) Resource partitioning along multiple niche axes drives functional diversity in parrotfishes on Caribbean coral reefs. Oecologia 179:1173–1185.

Asner GP, Vaughn NR, Balzotti C, Brodrick PG, Heckler J (2020) High-Resolution Reef Bathymetry and Coral Habitat Complexity from Airborne Imaging Spectroscopy. Remote Sens 12:310.

Baker AC, Glynn PW, Riegl B (2008) Climate change and coral reef bleaching: An ecological assessment of long-term impacts, recovery trends and future outlook. Estuar Coast Shelf Sci 80:435–471.

Battista TA, Costa BM, Anderson SM (2007) Shallow-water benthic habitats of the main eight Hawaiian Islands (DVD). NOAA Tech Memo NOS NCCOS 61.

Baum JK, Worm B (2009) Cascading top-down effects of changing oceanic predator abundances. J Anim Ecol 78:699–714.

Bellwood D, Hughes T, Folke C, Nyström M (2004) Confronting the coral reef crisis. Nature 429:827–833.

Bellwood DR, Choat JH (1990) A functional analysis of grazing in parrotfishes (family Scaridae): the ecological implications. Environ Biol fishes:189–214.

Bellwood DR, Hughes TP, Hoey AS (2006) Sleeping functional group drives coral-reef recovery. Curr Biol 16:2434–2439.

Beverton RJH, Holt SJ (1993) On the dynamics of exploited fish populations. Springer Science & Business Media.

Birkeland C, Dayton PK (2005) The importance in fishery management of leaving the big ones. Trends Ecol Evol 20:356–358.

Birrell CL, McCook LJ, Willis BL (2005) Effects of algal turfs and sediment on coral settlement. Mar Pollut Bull 51:408–414.

Birrell CL, McCook LJ, Willis BL, Diaz-Pulido GA (2008) Effects of benthic algae on the replenishment of corals and the implications for the resilience of coral reefs. Oceanogr Mar Biol An Annu Rev 46:25–63.

Boldt J, Martone R, Samhouri J, Perry R, Itoh S, Chung I, Takahasi M, Yoshie N (2014) Developing ecosystem indicators for responses to multiple stressors. Oceanography 27:116–133.

Bonaldo RM, Bellwood DR (2008) Size-dependent variation in the functional role of the parrotfish Scarus rivulatus on the Great Barrier Reef, Australia. Mar Ecol Prog Ser 360:237–244.

Bonaldo RM, Hoey AS, Bellwood DR (2014) The ecosystem roles of parrotfishes on tropical reefs. Oceanogr Mar Biol An Annu Rev 52:81–132.
Bruggemann JH, Kuyper MWM, Breeman AM (1994) Comparative analysis of foraging and habitat use by the sympatric Caribbean parrotfish Scarus vetula and Sparisoma viride (Scaridae). Mar Ecol Prog Ser 112:51–66.
Bruno J, Sweatman H, Precht W (2009) Assessing evidence of phase shifts from coral to macroalgal dominance on coral reefs. Ecology 90:1478–1484.
Burkepile DE, Hay ME (2008) Herbivore species richness and feeding complementarity affect community structure and function on a coral reef. Proc Natl Acad Sci 105:16201–16206.
Burkepile DE, Hay ME (2010) Impact of herbivore identity on algal succession and coral growth on a Caribbean reef. PLoS One 5:e8963.
Cinner JE, Huchery C, MacNeil MA, Graham NAJ, McClanahan TR, Maina J, Maire E, Kittinger JN, Hicks CC, Mora C (2016) Bright spots among the world's coral reefs. Nature 535:416–419.
Cole AJ, Pratchett MS, Jones GP (2008) Diversity and functional importance of coral-fe eding fishes on tropical coral reefs. Fish Fish 9:286–307.
Conklin EJ, Smith JE (2005) Abundance and spread of the invasive red algae, Kappaphycus spp., in Kane'ohe Bay, Hawai'i and an experimental assessment of management options. Biol Invasions 7:1029–1039.
Côté IM, Darling ES (2010) Rethinking ecosystem resilience in the face of climate change. PLoS Biol 8:e1000438.
Crosby MP, Reese ES (2005) Relationship of habitat stability and intra-specific population dynamics of an obligate corallivore butterflyfish. Aquat Conserv Mar Freshw Ecosyst 15.
Dierking J, Williams ID, Walsh WJ (2009) Diet composition and prey selection of the introduced grouper species peacock hind (Cephalopholis argus) in Hawaii. Fish Bull 107:464–476.
Donovan MK (2017) A synthesis of coral reef community structure in Hawaiʻi and the Caribbean. University of Hawaiʻi at Manoa
Donovan MK, Friedlander AM, Lecky J, Jouffray JB, Williams GJ, Wedding LM, Crowder LB, Erickson AL, Graham NAJ, Gove JM, Kappel C V., Karr K, Kittinger JN, Norström A V., Nyström M, Oleson KLL, Stamoulis KA, White C, Williams ID, Selkoe KA (2018) Combining fish and benthic communities into multiple regimes reveals complex reef dynamics. Sci Rep 8.
Dulvy NK, Freckleton RP, Polunin NVC (2004a) Coral reef cascades and the indirect effects of predator removal by exploitation. Ecol Lett 7:410–416.
Dulvy NK, Polunin NVC, Mill AC, Graham NAJ (2004b) Size structural change in lightly exploited coral reef fish communities: evidence for weak indirect effects. Can J Fish Aquat Sci 61:466–475.
Edwards CB, Friedlander AM, Green AG, Hardt MJ, Sala E, Sweatman HP,

Williams ID, Zgliczynski B, Sandin SA, Smith JE (2014) Global assessment of the status of coral reef herbivorous fishes: evidence for fishing effects. Proc R Soc B Biol Sci 281:20131835.
Fabricius KE (2005) Effects of terrestrial runoff on the ecology of corals and coral reefs: review and synthesis. Mar Pollut Bull 50:125–146.
Friedlander A, Sandin S, DeMartini E, Sala E (2010) Spatial patterns of the structure of reef fish assemblages at a pristine atoll in the central Pacific. Mar Ecol Prog Ser 410:219–231.
Friedlander AM, DeMartini EE (2002) Contrasts in density, size, and biomass of reef fishes between the northwestern and the main Hawaiian islands: the effects of fishing down apex predators. Mar Ecol Prog Ser 230:253–264.
Friedlander AM, Donovan MK, Stamoulis KA, Williams ID, Brown EK, Conklin EJ, Demartini EE, Rodgers KS, Sparks RT, Walsh WJ (2018) Human-induced gradients of reef fish declines in the Hawaiian Archipelago viewed through the lens of traditional management boundaries. Aquat Conserv Mar Freshw Ecosyst 28:146–157.
Friedlander AM, Parrish JD (1998) Habitat characteristics affecting fish assemblages on a Hawaiian coral reef. J Exp Mar Bio Ecol 224:1–30.
Gelman A, Rubin DB (1992) Inference from iterative simulation using multiple sequences. Stat Sci:457–472.
Giddens J, Friedlander AM, Conklin E, Wiggens C, Stamoluis K, Donovan MK (2014) Experimental removal of the invasive peacock hind (roi) Cephalopholis argus, in Puako, Hawaiʻi: methods for assessing and managing marine invasive species. Mar Ecol Prog Ser 511:209–211.
Giddens JL, Wiggins C, Friedlander AM, Conklin EJ, Stamoulis KA, Minton D (2018) Assemblage-level effects of the introduced peacock hind (Cephalopholis argus) on Hawaiian reef fishes. Environ Biol Fishes 101:275–286.
Goatley CHR, Bellwood DR (2010) Biologically mediated sediment fluxes on coral reefs: sediment removal and off-reef transportation by the surgeonfish Ctenochaetus striatus. Mar Ecol Prog Ser 415:237–245.
Gotelli NJ, Colwell RK (2011) Estimating species richness. Biol Divers Front Meas Assess 12:39–54.
Gove JM, Williams GJ, McManus MA, Heron SF, Sandin SA, Vetter OJ, Foley DG (2013) Quantifying climatological ranges and anomalies for Pacific coral reef ecosystems. PLoS One 8.
Grafeld S, Oleson KLL (2016) A value chain analysis of Hawaiʻi's commerical nearshore reef fishery.
Graham NAJ, Dulvy NK, Jennings S, Polunin NVC (2005) Size-spectra as indicators of the effects of fishing on coral reef fish assemblages. Coral Reefs 24:118–124.

Graham NAJ, Wilson SK, Jennings S, Polunin NVC, Robinson JAN, Bijoux JP, Daw TM (2007) Lag effects in the impacts of mass coral bleaching on coral reef fish, fisheries, and ecosystems. Conserv Biol 21:1291–1300.

Gray AE, Williams ID, Stamoulis KA, Boland RC, Lino KC, Hauk BB, Leonard JC, Rooney JJ, Asher JM, Lopes Jr KH (2016) Comparison of reef fish survey data gathered by open and closed circuit SCUBA divers reveals differences in areas with higher fishing pressure. PLoS One 11:e0167724.

Green AL, Bellwood DR (2009) Monitoring functional groups of herbivorous reef fishes as indicators of coral reef resilience - A practical guide for coral reef managers in the Asia Pacific Region.

Haddon M (2011) Modelling and Quantitative Methods in Fisheries. CRC Press:i–433.

Harrington L, Fabricius K, De'Ath G, Negri A (2004) Recognition and selection of settlement substrata determine post-settlement survival in corals. Ecology 85:3428–3437.

Hay ME (1984) Patterns of fish and urchin grazing on Caribbean coral reefs: are previous results typical? Ecology 65:446–454.

Hixon MA, Brostoff WN (1996) Succession and herbivory: Effects of differential fish grazing on Hawaiian coral-reef algae. Ecol Monogr 66:67 –90.

Holsman K, Samhouri J, Cook G, Hazen E, Olsen E, Dillard M, Kasperski S, Gaichas S, Kelble CR, Fogarty M (2017) An ecosystem-based approach to marine risk assessment. Ecosyst Heal Sustain 3.

Hourigan TF, Timothy CT, Reese ES (1988) Coral reef fishes as indicators of environmental stress in coral reefs. In: *Marine organisms as indicators*. Springer, p 107–135

Hughes TP, Baird AH, Bellwood DR (2003) Climate change, human impacts, and the resilience of coral reefs. Science 301:929–933.

Hughes TP, Graham NAJ, Jackson JBC, Mumby PJ, Steneck RS (2010) Rising to the challenge of sustaining coral reef resilience. Trends Ecol Evol 25:633–642.

Hughes TP, Rodrigues MJ, Bellwood DR (2007) Phase shifts, herbivory, and the resilience of coral reefs to climate change. Curr Biol 17:360–365.

Jokiel PL, Rodgers KS, Brown EK, Kenyon JC, Aeby G, Smith WR, Farrell F (2015) Comparison of methods used to estimate coral cover in the Hawaiian Islands. PeerJ 3:e954.

Jompa J, McCook LJ (2002) The effects of nutrients and herbivory on competition between a hard coral (Porites cylindrica) and a brown alga (Lobophora variegata). Limnol Oceanogr 47:527–534.

Jouffray JB, Nyström M, Norström A, Williams ID, Wedding LM, Kittinger JN, Williams GJ (2015) Identifying multiple coral reef regimes and their drivers across the Hawaiian archipelago. Philos Trans R Soc 370:20130268.

Karr KA, Fujita R, Halpern BS, Kappel C V, Crowder L, Selkoe KA, Alcolado PM, Rader D (2015) Thresholds in Caribbean coral reefs: implications for ecosystem-based fishery management. J Appl Ecol 52 :402–412.
Kershner J, Samhouri JF, James CA, Levin PS (2011) Selecting indicator portfolios for marine species and food webs: a Puget Sound case study. PLoS One 6:e25248.
Kittinger JN, Teneva LT, Koike H, Stamoulis KA, Kittinger DS, Oleson KLL, Conklin E, Gomes M, Wilcox B, Friedlander AM (2015) From reef to table: Social and ecological factors affecting coral reef fisheries, artisanal seafood supply chains, and seafood security. PLoS One 10:e0123856.
Kuffner IB, Walters LJ, Becerro MA, Paul VJ, Ritson-Williams R, Beach KS (2006) Inhibition of coral recruitment by macroalgae and cyanobacteria. Mar Ecol Prog Ser 323:107–117.
Lecky J (2016) Ecosystem vulnerability and mapping cumulative impacts on Hawaiian reefs. University of Hawaii at Manoa
Lewis SM, Wainwright PC (1985) Herbivore abundance and grazing intensity on a Caribbean coral reef. J Exp Mar Bio Ecol 87:215–228.
Loya Y, Sakai K, Yamazato K, Nakano Y, Sambali H, van Woesik R (2001) Coral bleaching: the winners and the losers. Ecol Lett 4:122–131.
MacNeil MA, Graham NAJ, Cinner JE, Wilson SK, Williams ID, Maina J, Newman S, Friedlander AM, Jupiter S, Polunin NVC (2015) Recovery potential of the world’s coral reef fishes. Nature 520:341–344.
Madin EMP, Gaines SD, Warner RR (2010) Field evidence for pervasive indirect effects of fishing on prey foraging behavior. Ecology 91:3563–3571.
Malo D (1951) Moolelo Hawaii-Hawaiian Antiquities. Bishop Museum.
Marshell A, Mumby PJ (2012) Revisiting the functional roles of the surgeonfish Acanthurus nigrofuscus and Ctenochaetus striatus. Coral Reefs 31:1093–1101.
Martinez JA, Smith CM, Richmond RH (2012) Invasive algal mats degrade coral reef physical habitat quality. Estuar Coast Shelf Sci 99:42–49.
McClanahan T, Maina JM, Muthiga NA (2011a) Associations between climate stress and coral reef diversity in the western Indian Ocean. Glob Chang Biol 17:2023–2032.
McClanahan TR, Graham NAJ, MacNeil MA, Cinner JE (2015) Biomass-based targets and the management of multispecies coral reef fisheries. Conserv Biol 29:409–417.
McClanahan TR, Graham NAJ, MacNeil MA, Muthiga NA, Cinner JE, Bruggemann JH, Wilson SK (2011b) Critical thresholds and tangible targets for ecosystem-based management of coral reef fisheries. Proc Natl Acad Sci U S A 108:17230–17233.
McCook L, Jompa J, Diaz-Pulido G (2001) Competition between corals and

algae on coral reefs: a review of evidence and mechanisms. Coral reefs 19:400–417.
McCoy KS, Williams ID, Friedlander AM, Ma H, Teneva L, Kittinger JN (2018) Estimating nearshore coral reef-associated fisheries production from the main Hawaiian Islands. PLoS One 13:e0195840.
MEA (2005) Millenium Ecosystem Assessment: Ecosystems and human well-being: wetlands and water. World Resour Institute, Washington, DC 5.
Mumby PJ, Bejarano S, Golbuu Y, Steneck RS, Arnold SN, van Woesik R, Friedlander AM (2013a) Empirical relationships among resilience indicators on Micronesian reefs. Coral Reefs 32:213–226.
Mumby PJ, Dahlgren C, Harborne A (2006) Fishing, trophic cascades, and the process of grazing on coral reefs. Science 311:98–101.
Mumby PJ, Hastings A, Edwards HJ (2007) Thresholds and the resilience of Caribbean coral reefs. Nature 450:98–101.
Mumby PJ, Steneck RS, Hastings A (2013b) Evidence for and against the existence of alternate attractors on coral reefs. Oikos 122:481–491.
Nadon MO (2014) Improving Stock Assessment Capabilities for the Coral Reef Fishes of Hawaii and the Pacific Region. University of Miami. University of Miami
Nadon MO, Ault JS, Williams ID, Smith SG, DiNardo GT (2015) Length-Based Assessment of Coral Reef Fish Populations in the Main and Northwestern Hawaiian Islands. PLoS One 10:e0133960.
Nash KL, Bijoux J, Robinson J, Wilson SK, Graham NAJ (2016) Harnessing fishery-independent indicators to aid management of data - poor fisheries: weighing habitat and fishing effects. Ecosphere 7.
Neilson BJ, Wall CB, Mancini FT, Gewecke CA (no date) Herbivore biocontrol and manual removal successfully reduce invasive macroalgae on coral reefs. PeerJ.
Norström A V, Nyström M, Lokrantz J, Folke C (2009) Alternative states on coral reefs: Beyond coral-macroalgal phase shifts. Mar Ecol Prog Ser 376:293–306.
Nugues MM, Bak RPM (2006) Differential competitive abilities between Caribbean coral species and a brown alga: a year of experiments and a long-term perspective. Mar Ecol Prog Ser 315:75–86.
Nugues MM, Smith GW, Hooidonk RJ, Seabra MI, Bak RPM (2004) Algal contact as a trigger for coral disease. Ecol Lett 7:919–923.
Nyström M, Graham N, Lokrantz J, Norström A (2008) Capturing the cornerstones of coral reef resilience: Linking theory to practice. Coral Reefs 27:795–809.
Peters RH (1986) The ecological implications of body size. Cambridge University Press.

Peterson G, Allen CR, Holling CS (1998) Ecological resilience, biodiversity, and scale. Ecosystems 1:6–18.
Plummer M (2016) Rjags: Bayesian Graphical Models using MCMC. R package version 4-6. https://CRAN.R-project.org/package=rjags
Pratchett MS, Wilson SK, Baird AH (2006) Declines in the abundance of Chaetodon butterflyfishes following extensive coral depletion. J Fish Biol 69:1269–1280.
Price N (2010) Habitat selection, facilitation, and biotic settlement cues affect distribution and performance of coral recruits in French Polynesia. Oecologia 163:747–758.
Randall JE (1987) Introductions of marine fishes to the Hawaiian Islands. Bull Mar Sci 41:490–502.
Rasher DB, Hay ME (2010) Chemically rich seaweeds poison corals when not controlled by herbivores. Proc Natl Acad Sci 107:9683–9688.
Reese ES (1977) Coevolution of corals and coral feeding fishes of the family Chaetodontidae. In: *Proc 3rd Int Coral Reef Symp*. p 267–274
Reese ES (1981) Predation on corals by fishes of the family Chaetodontidae: implications for conservation and management of coral reef ecosystems. Bull Mar Sci 31:594–604.
Richards BL, Williams ID, Nadon MO, Zgliczynski BJ (2011) A towed-diver survey method for mesoscale fishery-independent assessment of large-bodied reef fishes. Bull Mar Sci 87:55–74.
Robinson JPW, Williams ID, Edwards AM, McPherson J, Yeager L, Vigliola L, Brainard RE, Baum JK (2017) Fishing degrades size structure of coral reef fish communities. Glob Chang Biol 23:1009–1022.
Rodgers S, Cox EF (1999) Rate of Spread of Introduced Rhodophytes Kappaphycus alvarezii, Kappaphycus striatum, and Gracilaria salicornia and Their Current Distribution in Kane’ohe Bay, O’ahu Hawai’i.
Ruttenberg BI, Hamilton SL, Walsh SM, Donovan MK, Friedlander A, DeMartini E, Sala E, Sandin SA (2011) Predator-induced demographic shifts in coral reef fish assemblages. PLoS One 6:e21062.
Sandin SA, Smith JE, DeMartini EE, Dinsdale EA, Donner SD, Friedlander AM, Konotchick T, Malay M, Maragos JE, Obura D, Pantos O, Paulay G, Richie M, Rohwer F, Schroeder RE, Walsh S, Jackson JBC, Knowlton N, Sala E (2008) Baselines and degradation of coral reefs in the Northern Line Islands. PLoS One 3:e1548.
Sandin SA, Walsh SM, Jackson JBC (2010) Prey release, trophic cascades, and phase shifts in tropical nearshore ecosystems. Trophic Cascades predators, prey, Chang Dyn Nat:71–90.
Smith JE, Brainard R, Carter A, Grillo S, Edwards C, Harris J, Lewis L, Obura D, Rohwer F, Sala E (2016) Re-evaluating the health of coral reef

communities: baselines and evidence for human impacts across the central Pacific. Proc R Soc B Biol Sci 283:20151985.
Smith JE, Hunter CL, Smith CM (2010) The effects of top-down versus bottom-up control on benthic coral reef community structure. Oecologia 163:497–507.
Smith JE, Shaw M, Edwards RA, Obura D, Pantos O, Sala E, Sandin SA, Smriga S, Hatay M, Rohwer FL (2006) Indirect effects of algae on coral: algae-mediated, microbe- induced coral mortality. Ecol Lett 9:835 –845.
Steneck RS (1988) Herbivory on coral reefs: a synthesis. In: *Proc 6th Int Coral Reef Symp*. p 37–49
Steneck RS (1986) The ecology of coralline algal crusts: convergent patterns and adaptative strategies. Annu Rev Ecol Syst 17:273–303.
Stimson J, Larned S, Conklin E (2001) Effects of herbivory, nutrient levels, and introduced algae on the distribution and abundance of the invasive macroalga Dictyosphaeria cavernosa in Kaneohe Bay, Hawaii. Coral Reefs 19:343–357.
Vallès H, Oxenford H a (2014) Parrotfish size: a simple yet useful alternative indicator of fishing effects on Caribbean reefs? PLoS One 9:e86291.
Vermeij MJA, Dailer ML, Walsh SM, Donovan MK, Smith CM (2010) The effects of trophic interactions and spatial competition on algal community composition on Hawaiian coral reefs. Mar Ecol 31:291–299.
Vermeij MJA, Sandin SA (2008) Density-dependent settlement and mortality structure the earliest life phases of a coral population. Ecology 89:1994–2004.
Vermeij MJA, Smith JE, Smith CM, Thurber RV, Sandin SA (2009) Survival and settlement success of coral planulae: independent and synergistic effects of macroalgae and microbes. Oecologia 159:325–336.
Vroom PS, Braun CL (2010) Benthic composition of a healthy subtropical reef: baseline species-level cover, with an emphasis on algae, in the Northwestern Hawaiian Islands. PLoS One 5:e9733.
Walsh SM, Hamilton SL, Ruttenberg BI, Donovan MK, Sandin SA (2012) Fishing top predators indirectly affects condition and reproduction in a reef-fish community. J Fish Biol.
Warwick R (1986) A new method for detecting pollution effects on marine macrobenthic communities. Mar Biol 92:557–562.
Wedding LM, Lecky J, Gove JM, Walecka H, Donovan MK, Williams GJ, Jouffray J, Crowder LB, Erickson AL, Falinski K, Friedlander AM, Kappel C V, Kittinger JN, McCoy K, Norström A V, Nyström M, Oleson KLL, Stamoulis KA, White C, Selkoe KA (2018) Advancing the Integration of Spatial Data to Map Human and Natural Drivers on Coral Reefs. PLoS One in press.
Weil E, Croquer A, Urreiztieta I, Irizarry E (2009) Temporal variability and

impact of coral diseases and bleaching in La Parguera, Puerto Rico from 2003–2007. Caribb J Sci 45:221–246.
Williams ID, Baum JK, Heenan A, Hanson KM, Nadon MO, Brainard RE (2015) Human, oceanographic and habitat drivers of Central and Western Pacific coral reef fish assemblages. PLoS One 10:e0120516.
Williams ID, Polunin N (2001) Large-scale associations between macroalgal cover and grazer biomass on mid-depth reefs in the Caribbean. Coral reefs 19:358–366.
Williams ID, Walsh WJ, Schroeder RE, Friedlander AM, Richards BL, Stamoulis KA (2008) Assessing the importance of fishing impacts on Hawaiian coral reef fish assemblages along regional-scale human population gradients. Environ Conserv 35:261.
Williams ID, White DJ, Sparks RT, Lino KC, Zamzow JP, Kelly ELA, Ramey HL (2016) Responses of Herbivorous Fishes and Benthos to 6 Years of Protection at the Kahekili Herbivore Fisheries Management Area, Maui. PLoS One 11:e0159100.
Winter KB, Beamer K, Vaughan MB, Friedlander AM, Kido MH, Whitehead AN, Akutagawa MKH, Kurashima N, Lucas MP, Nyberg B (2018) The Moku System: Managing biocultural resources for abundance within social-ecological regions in Hawaiʻi. Sustainability 10:3554.
Zgliczynski BJ, Sandin SA (2016) Size-structural shifts reveal intensity of exploitation in coral reef fisheries. Ecol Indic 73:411–421.

Appendix 1 – Data Integration Process

A. Data Request

An email is sent to each data partner organization requesting their fish and benthic data for a specific date range and initiating the QAQC conversation. Specifically, the email explains that HIMARC will format and run through an initial QAQC with each set of data and follow-up with any questions or potential errors identified in the initial QAQC process.

B. Data Formatting and QAQC

As HIMARC works through the data formatting and initial QAQC, a record of the process is created and retained. This record includes thorough notes on how the data has been interpreted, re-formatted, and processed through data-checking scripts. In addition, questions or potential errors are highlighted. This record is compiled as a report and shared with the data partner.

1. **Review data set(s) provided to ensure clear interpretation of the original data column names and overall structure.** Data is often provided to HIMARC in multiple data tables. These data tables may reflect data collection by region, photo analysis output data files, or a collection of tables linked together from database software. Some surveys are performed at permanent locations while others are at randomized locations. Some teams collect one set of data per location per survey, while others collect four or more sets of data per survey location. When data files are first received, the files are carefully reviewed to elicit the overall data structure. As part of this process, HIMARC merges files from the data provider to create one fish survey data file and one benthic survey data file that incorporate all metadata and survey locations. As needed, originally separate files are linked based on survey metadata (for example, the site location and habitat details are in one or a few data tables, while the fish observations are in a separate data table, we link these files together based on the survey ID).

2. **Transform data set(s) into a consistent format while retaining key features of original data structure.** HIMARC modifies data column

names to align with the HIMARC database naming conventions. Given the different sampling design of each data partner, this step requires careful attention to detail and detailed understanding of the survey structure and data files provided. For example, some surveys have multiple divers collecting data (these will ultimately need to be added together to consider the data from each survey) while others have multiple divers surveying unique surveys at the same location (these will ultimately need to be averaged to consider the data from that location on that day). For the benthic data, some teams share data at the photo scale, while others provide the data at the site location scale. These differences are critical to the appropriate integration into the HIMARC database and, ultimately, the correct interpretation of analyses based on the HIMARC database.

3. **Run through a thorough QAQC process to identify any missing data, potential errors, and duplicated data.** This step is further broken down into site scale parameters and observation scale parameters.
    a. <u>Site Scale Parameters:</u> Any questions or errors at the site scale can lead to entire surveys being incorrect or requiring elimination from the database. Clarifying issues at this scale is of critical importance – without key site-scale data, the surveys cannot be used.
        i. HIMARC creates a table of the number of unique surveys by year (and survey region, when applicable) and shares this with the data partner to verify that the total number of unique surveys matches data provider expectations.
        ii. HIMARC investigates the locations of each survey. We verify that each survey includes a latitude and longitude, and we map all points to verify that these are in the domain (occasionally formatting discrepancies or data entry errors result in data points that are not within coastal Hawaiian habitats). Any points with missing or unusual location information are documented and the maps of survey locations are incorporated in the QAQC report document to be shared with the data provider.
        iii. HIMARC reviews the survey date, depth, and rugosity information included with the survey. To be incorporated in the database, each survey must be associated with a year (ideally

a month and day as well). Occasionally formatting discrepancies or data entry errors result in erroneous survey dates. These are identified and any issues are shared with the data provider. When provided, depth and rugosity information are checked to ensure that the values fall within reasonable ranges, the units are interpretable, and any 0 values are identified. Zero values for depth or rugosity generally are miscoded NAs; these are confirmed with the data provider and changed to NA as appropriate.

iv. Finally, HIMARC considers diver IDs as well as any provided habitat details. We create a table with the number of surveys for each unique diver ID. We consider whether each diver ID is truly unique or if a diver sometimes used different IDs, as well as identifying any diver IDs that have only surveyed one or a few surveys suggesting this diver ID may be a typo. For habitat information, we include a variety of levels of habitat information in the HIMARC database reflecting what is provided by different data partners. These include reef zone, reef habitat, and habitat category. We review any habitat information provided, use provided data to create more inclusive category scales when possible, identify any novel habitat codes to clarify definitions with the data provider, and identify any major gaps in habitat information to include in our conversation with the data provider. Sometimes no habitat information is directly provided with the survey data, but surveys are restricted to specific habitat categories; in these cases, data providers who are familiar with the survey sites can often provide additional habitat information.

b. <u>Observation Scale Parameters:</u> Observation scale errors are generally either discrepancies in species identity codes or size ranges between data provider teams or data entry errors that can be corrected through a review of the raw survey data. If not corrected, these errors can often be reasonably adjusted to still retain these data (e.g., an unclear species code can be adjusted to a family level observation, an out-of-range size can be adjusted to the mean size for that species, etc.).

i. HIMARC reviews the species IDs used in the data file. We run a match to see if any of the IDs do not match codes previously used, and we note any codes that have not been previously defined or that appear to not be Hawaiian species. We also note any small differences in species names between the data provided and our master species file to enable a conversation about these differences such that at a minimum, both the data provider and HIMARC know that different names are being used, or more ideally, we reach a consensus.

ii. Then, HIMARC checks the total length size estimates for fish observations. To check for observations that are out-of-range, we compare observed sizes to 110% of the max size + 5cm (where the max size is based on a reference table created from widely available databases, including WoRMS (World Register of Marine Species. 2020. available from http://www.marinespecies.org at VLIZ doi:10.14284/170), FishBase (Froese & Pauly, ed. 2019. FishBase: World Wide Web electronic publication. www.fishbase.org), and Randall (Reef and Shore Fishes of the Hawaiian Islands 2007, Reef and Shore Fishes of the South Pacific 2005). This process flags unrealistically large observations for each taxon using the maximum known size for each species plus some variation. (Note that correcting for large, out-of-range individual observations is critical because biomass calculations are more sensitive to larger individuals). Often fish that are identified as “too big” are actually data entry errors either on the size or the species ID. We note these observations with the survey data, diver ID, location information, and other site metadata, and we ask the data partner to check the original datasheets on these observations when possible. To check for observations that are notably small, we identify any observations of size 0 cm in the data. Then, we compare observed sizes to 25% of the observed mean size minus 5cm (where the mean size is a species-specific estimate calculated based observations of each species within the provided dataset). In addition, we run a check for all elasmobranchs based pup size of each species reported in the literature.

iii. Next, HIMARC reviews fish counts by species. While “too many” is harder to clearly define than “too big”, NOAA has assembled a list of max counts by species. We use this max count + 5, and run a check on the number of fish in each observation to get a sense of potentially problematic observations.

iv. Finally, HIMARC checks for duplicated survey datasets in which the exact same data has been provided multiple times. We run this check for surveys that have matching site level and observation level data (a full data sheet was potentially entered twice) as well as for surveys that have different site level data and observation level data (the same data was potentially entered under multiple site naming schemes).

C. Discuss Data QAQC Report with Data Partner

The full data QAQC report is shared with the data partner. This document includes a record of the data review, formatting, and QAQC process, and highlights any questions or potential errors to discuss with the data provider. Working with the data partner we fill in gaps in the data, clarify questions on the data, and update both the original version and the HIMARC version of these data. Depending on the quantity and complexity of the questions with a given data set, this process can result in a revised data set being created and a second run through the “Data Formatting and QAQC” sets previously described. For some data sets, we work together with data providers through multiple iterations of this process to reach a finalized version of the data.

D. Share HIMARC Formatted Dataset with Data Partner

Once the QAQC process is completed, HIMARC shares a final copy of the report with the partner. This final copy of the report includes various comments and responses documenting the conversations had throughout the process. In addition, HIMARC shares a csv file of the data provider’s dataset(s) in the HIMARC format. We find this format agreeable for quickly subsetting the data and for running analyses in R and Excel, so we welcome the data partner to use these formatted data as desired. When data was originally provided to HIMARC in multiple files, we also strive to provide the data partner with these raw data merged into a singular file. When requested, HIMARC adds notation to the R code developed and used for the QAQC process and shares these code files with the data partner.

E. Merge QAQCed and Formatted Datasets into HIMARC Database

Once data is QAQCed and formatted following the above steps, it can be integrated into the HIMARC database. As part of this step, a final QAQC is run with a focus on identifying any duplicates of data from instances where multiple data providers were working together on surveys and both provide the same data or where the time frame of data provided overlaps previous data shared with HIMARC.

F. Calibrate Across the Distinct Survey Methods for Fish Surveys

With all of the statewide monitoring in one location and one format, the final step required before these data can be used collectively in analyses is to calibrate across the different survey methods. Previous analyses have found no large bias associated with percent cover among the benthic methods used by data partners (Jokiel et al. 2015). Alternatively, differences in the fish survey methods used by partner organizations across the state of Hawaiʻi are connected with species-specific biases in the density of fish observed.

The calibration method HIMARC is currently using was developed following the best available practices in 2013-2014 through a team effort in which HIMARC worked closely with personnel at UH and NOAA. While we are still utilizing this method, we have identified gaps in this calibration and recognize the importance of updating this survey method calibration in the near future. In addition to taking advantage of advances in computing capacity and statistical software, updating the calibration is critical to account for the updated suite of fish observation data available across spatial and temporal scales. This calibration update is a high priority for HIMARC as it is a critical step in curating a statewide database reliant on data from multiple organizations to guide management decisions. Updating the calibration requires devoted, highly trained personnel.

To calibrate the fish survey data, HIMARC uses the NOAA Biogeography Program belt transect as the base method (this method had the greatest consistency with other program survey methods, (Friedlander et al. 2018)) and then standardizes each of the other survey methods using calibration factors (Donovan et al. 2018). These calibration factors were developed using an automated software program that utilized general linear models and Monte Carlo simulations (Nadon 2014) based on data integrated into the HIMARC database by 2014.

Calibration factors were calculated by species where possible based on the following decision rules: (1) a minimum of 10 paired (between survey methods) observations were available within an island, (2) observations are not dominated by zeros – if they were, a delta model was run in which occurrences were modeled separately from non-occurrences, (3) residuals were normally distributed – if not, data were log-transformed and the model was rerun and checked again. For the subset of species that did not pass this series of rules, a calibration factor was calculated for each combination of family and trophic level (e.g., zooplanktivorous wrasses). If the decision rules were not satisfied at the family and trophic level, then a global calibration factor calculated for all fish observed with the specific survey method was used for this subset of fish species.

Appendix 2 – Indicator selection data

Candidate Indicators

Score	Indicator	Measurable with existing database	Theoretical soundness	Relevance to management concerns	Known responsive-ness to management interventions	Interp-retability by policy makers and public	Background and References
Fish assemblage							
1	Total fish biomass	1	1	1	1	1	Total fish biomass is an indicator of trophic structure (McClanahan et al. 2015), stock status (Beverton & Holt 1993), and recovery potential (MacNeil et al. 2015). Several examples exist for trends in total fish biomass across human impact gradients for Hawaiian reef fishes (Friedlander & DeMartini 2002, Williams et al. 2008, 2015, Friedlander et al. 2010), as well as for using total biomass as an indicator of ecosystem condition (McClanahan et al. 2011b, Karr et al. 2015).
0.75	Total fish biomass (excluding sharks/jacks)	1	0.5	1	1	0.5	Sharks and jacks are highly mobile predators that may have different responses to the presence of divers depending on location, therefore removing those species from calculations of overall biomass may be a less biased indicator (Richards et al. 2011, Williams et al. 2015,

							Gray et al. 2016). Thus, this metric represents biomass of the assemblage that is ‘site-attached’. This metric has been used in global assessments to show differences in management effectiveness and recovery time for reef fishes (MacNeil et al. 2015, Cinner et al. 2016).
0.875	Total fish abundance	1	0.5	1	0	1	Total fish abundance the overall numerical density for the entire fish assemblage, and thus serves as the coarsest indicator of the fish assemblage. Biomass provides an extra level of detail by combining numerical density with fish size, and numerical and biomass densities are not necessarily linearly correlated (Warwick 1986).
0.375	Non-resource fish biomass	1	1	0	0	0.5	Non-resource fish biomass is the remainder of the total biomass not comprised of resource fish. This metric has been used to test alternative hypotheses associated with fish populations other than fishing effects (Williams et al. 2008, Friedlander et al. 2018). However, it is not specific to a particular component of the fish assemblage or a specific hypothesized human impact, so may be less useful than other indicators.
0.375	Secondary Consumer Biomass	1	0.5	0.5	0.5	0	Patterns across gradients of human impacts are mixed, for example there was no difference in biomass between the main and northwestern Hawaiian Islands (Friedlander & DeMartini 2002), but were

							lower in the populated Line islands (Sandin et al. 2008).
0.25	Planktivore Biomass	1	0.5	0	0.5	0	Planktivore abundance can makeup a large proportion of overall biomass of Hawaiian reef fish assemblages (Friedlander & Parrish 1998, Friedlander & DeMartini 2002). However estimating biomass of planktivores with underwater visual surveys is difficult due to their clumped distributions that result from behavioral factors related to feeding where plankton aggregates.
Food fish							
1	Size structure fish assemblage (mean adult size or size-spectra exponent)	1	1	1	1	1	Body size is an important predictor of ecological dynamics (Peters 1986), as well as an indicator of overall exploitation in fish communities (Dulvy et al. 2004b, Graham et al. 2005, Nash et al. 2016, Zgliczynski & Sandin 2016, Robinson et al. 2017). Size spectra has been shown to be an effective indicator of exploitation impacts on reefs, and has a comparatively lower sensitive to environmental gradients than biomass (Robinson et al. 2017). Mean adult size is an effective indication of size structure and has been shown also be a responsive indicator of exploitation impacts on reefs (Nadon et al. 2015, Nash et al. 2016, Zgliczynski & Sandin 2016).
1	Resource Fish Biomass	1	1	1	1	1	Resource fish biomass is a measure of the overall abundance of species targeted in local fisheries, and fisheries are a major component of the social and ecological

							wellbeing of the people of Hawai‘i. Therefore, resource fish biomass is a good indicator of the social-ecological system in Hawaii (Williams et al. 2008, Kittinger et al. 2015, Grafeld & Oleson 2016, Friedlander et al. 2018).
1	Prime Spawner Biomass	1	1	1	1	1	Prime spawner biomass was used by Williams et al. (2008) to represent the importance of breeding individuals of target fish, and was defined as biomass of target fish >70% of the maximum length for the species. This method was designed to reflect the greater contribution of large individuals to spawning potential for fish populations (Birkeland & Dayton 2005). The abundance of spawners is also an important metric in fisheries science, and forms an important component of stock assessments (Haddon 2011).
Herbivory							
1	Total Herbivore Biomass	1	1	1	1	1	Herbivores consists of several groups (above) that play complementary and redundant roles in maintaining ecological resilience on reefs (Hay 1984, Lewis & Wainwright 1985, Hixon & Brostoff 1996, Williams & Polunin 2001, Bellwood et al. 2004, Mumby et al. 2006, 2007, Hughes et al. 2007, Nyström et al. 2008, Burkepile & Hay 2008, 2010, Smith et al. 2010, 2016, Vermeij et al. 2010, Bonaldo et al. 2014, Edwards et al. 2014, Adam et al. 2015a). The biomass of herbivores has also been

							directly linked to reef resilience in Hawai‘i (Mumby et al. 2013a).
0.875	Biomass of parrotfish > 25 cm	1	1	1	1	0.5	Rates of herbivory by parrotfishes has been shown to be non-linear with body size, and increases rapidly after 25 cm (Bruggemann et al. 1994, Bonaldo & Bellwood 2008, Adam et al. 2015b). Parrotfish size has also been shown to be an effective indicator of fishing effects on reefs (Vallès & Oxenford 2014).
0.75	Scraper Biomass	1	1	1	1	0	Scrapers include large and small excavators and bioeroders that remove algae and sediment from coral surfaces (Steneck 1988, Bellwood & Choat 1990, Bonaldo et al. 2014). Larger individuals can also remove pieces of the coral, which makes space for coral recruits (Steneck 1988, Bellwood et al. 2004).
0.625	Grazer/Detritivore Biomass	1	1	0.5	1	0	Grazing herbivores feed on algal turfs, which often consists of young macroalgal species. Therefore, grazers are important for limiting the establishment and growth of macroalgae (Green & Bellwood 2009, Goatley & Bellwood 2010, Marshell & Mumby 2012).
0.625	Browser Biomass	1	1	0.5	1	0	Browsing herbivores feed directly on macroalgae, and therefore play an important role in reducing macroalgal cover (Bellwood et al. 2006).
Resilience							
1	% CCA cover	1	1	1	1	1	Crustose coralline algae (CCA) are a significant component of reef accretion, and

							make up a substantial proportion of the reef framework given their ability to fill interstitial space and bind together carbonate substrates (Steneck 1986). CCA have also been shown to be important for the recruitment and settlement of corals (Harrington et al. 2004, Vermeij et al. 2009, Price 2010). Likewise, CCA may be an important leading indicator of reef resilience, as measurable increases in cover have been documented in response to resilience based management measures (Williams et al. 2016).
0.75	% of coral resistant to bleaching	1	1	1	0.5	0.5	Particular species are resistant to bleaching during extreme temperature events, so a site with a high proportion of resistant taxa will be more resilient (resistant) to future events (Loya et al. 2001, Hughes et al. 2003, Baker et al. 2008).
0.625	Corallivore fish abundance	1	1	1	0.5	0	Obligate corallivores depend on live coral for food, and therefore their abundance is tightly linked with live coral cover (Crosby & Reese 2005, Cole et al. 2008). Thus, they have long been proposed as an indicator of reef status (Reese 1977, 1981, Hourigan et al. 1988), and their abundance has been linked with declines in reef status following disturbance (Pratchett et al. 2006, Graham et al. 2007).
Biodiversity							
0.75	Fish species richness	1	0.5	1	0.5	1	Diversity is often associated with intrinsic value of the ecosystem and further

							supports human wellbeing as a supporting ecosystem service (MEA 2005). Species richness is predicted to support ecosystem health based on the hypothesis that more species will support a greater number of critical ecosystem functions (Peterson et al. 1998). However, richness is difficult to measure as it is sensitive to sampling effects (Gotelli & Colwell 2011).
0.625	Non-native algae cover	1	0.5	1	0	1	Invasive macroalgae can have potentially large negative effects on reefs by outcompeting corals and other native benthic species, and intensifying other threats such as retaining sentiment or reducing herbivory (Stimson et al. 2001, Fabricius 2005, Rasher & Hay 2010). Several species of macroalgae are invasive in Hawaiʻi (Rodgers & Cox 1999, Conklin & Smith 2005, Martinez et al. 2012), and mitigation measures are underway to control for their spread (Neilson et al.).
0.375	Coral species richness	1	0.5	0.5	0	0.5	Resilience theory predicts that diversity is correlated with resilience (Peterson et al. 1998). However, evidence for this relationship in corals remains limited (McClanahan et al. 2011a), and support of theory is mixed (Nyström et al. 2008, Côté & Darling 2010). Additionally, Hawaiʻi generally has fewer numbers of coral species compared to a more species rich area, and spatially species richness doesn't

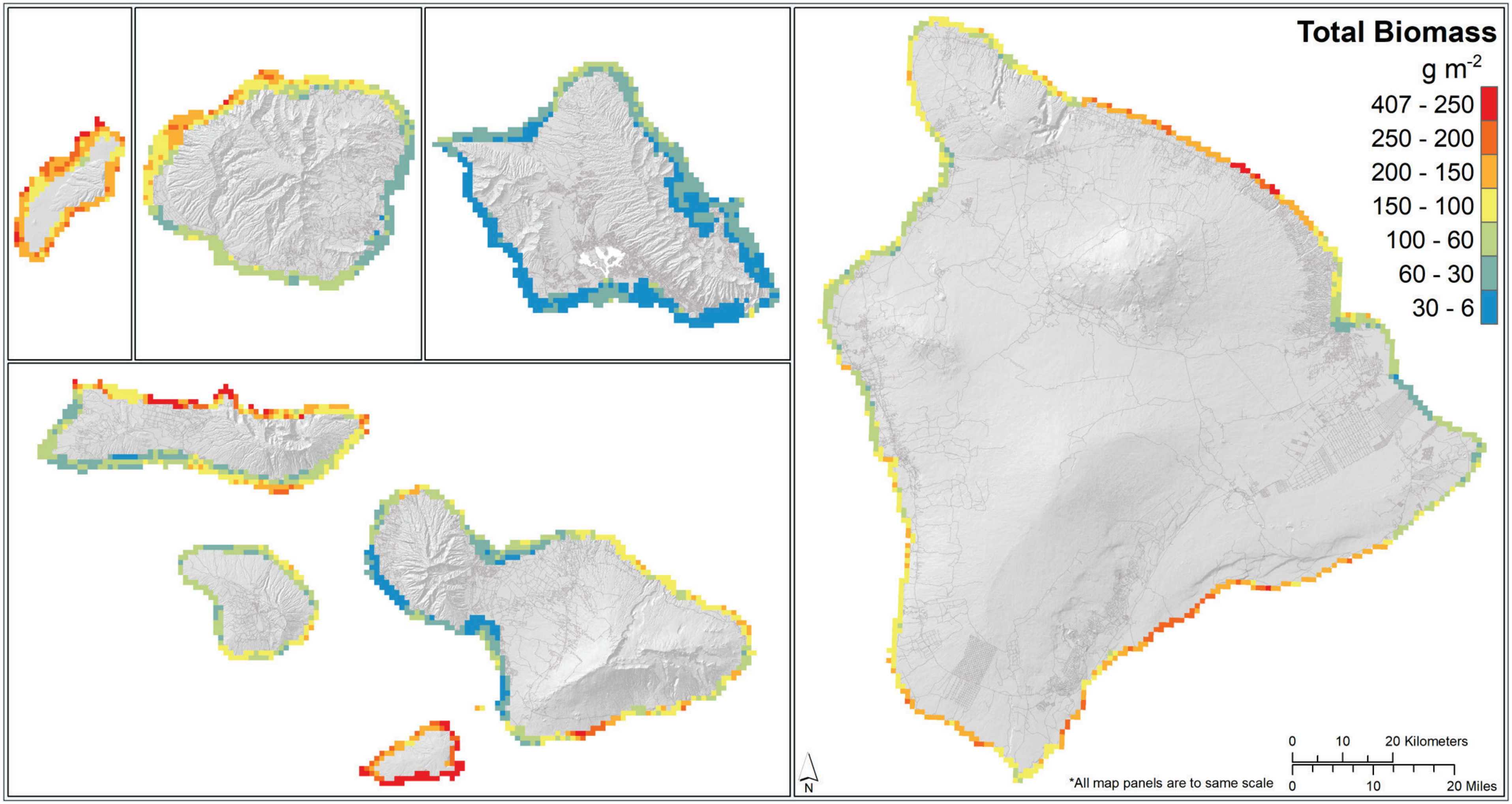
							vary greatly, so this metric may not effectively detect change.
0.375	Non-native fish abundance	1	0	0.5	0	1	Several species of reef associated fishes were introduced to Hawai‘i in the 1950s with the intention of providing additional fisheries targets. Three of the species, including a grouper (*Cephalophlis argus*), and two snappers (*Lutjanus kasmira*, and *L. fulvus*) have become established throughout the state of Hawai‘i (Randall 1987). *C. argus* has received attention as an invasive species due to its potentially negative role as a predator of native fishes (Dierking et al. 2009, Giddens et al. 2014). However, evidence of assemblage level impacts to date is equivocal (Giddens et al. 2018).
Trophic Structure							
0.875	Predator Biomass	1	1	1	1	0.5	Predators play an important role in maintaining ecosystem structure through direct (Friedlander & DeMartini 2002, Dulvy et al. 2004a, Baum & Worm 2009, Sandin et al. 2010), and indirect (Madin et al. 2010, Ruttenberg et al. 2011, Walsh et al. 2012) top down effects. Predatory species also tend to be fishery targets, so gradients of predator biomass correlate with gradients of human impacts (Friedlander & DeMartini 2002, Sandin et al. 2008, Williams et al. 2015).
0.75	Predator abundance	1	0.5	1	1	0.5	Predators can also be measured in terms of numerical density. However, given that

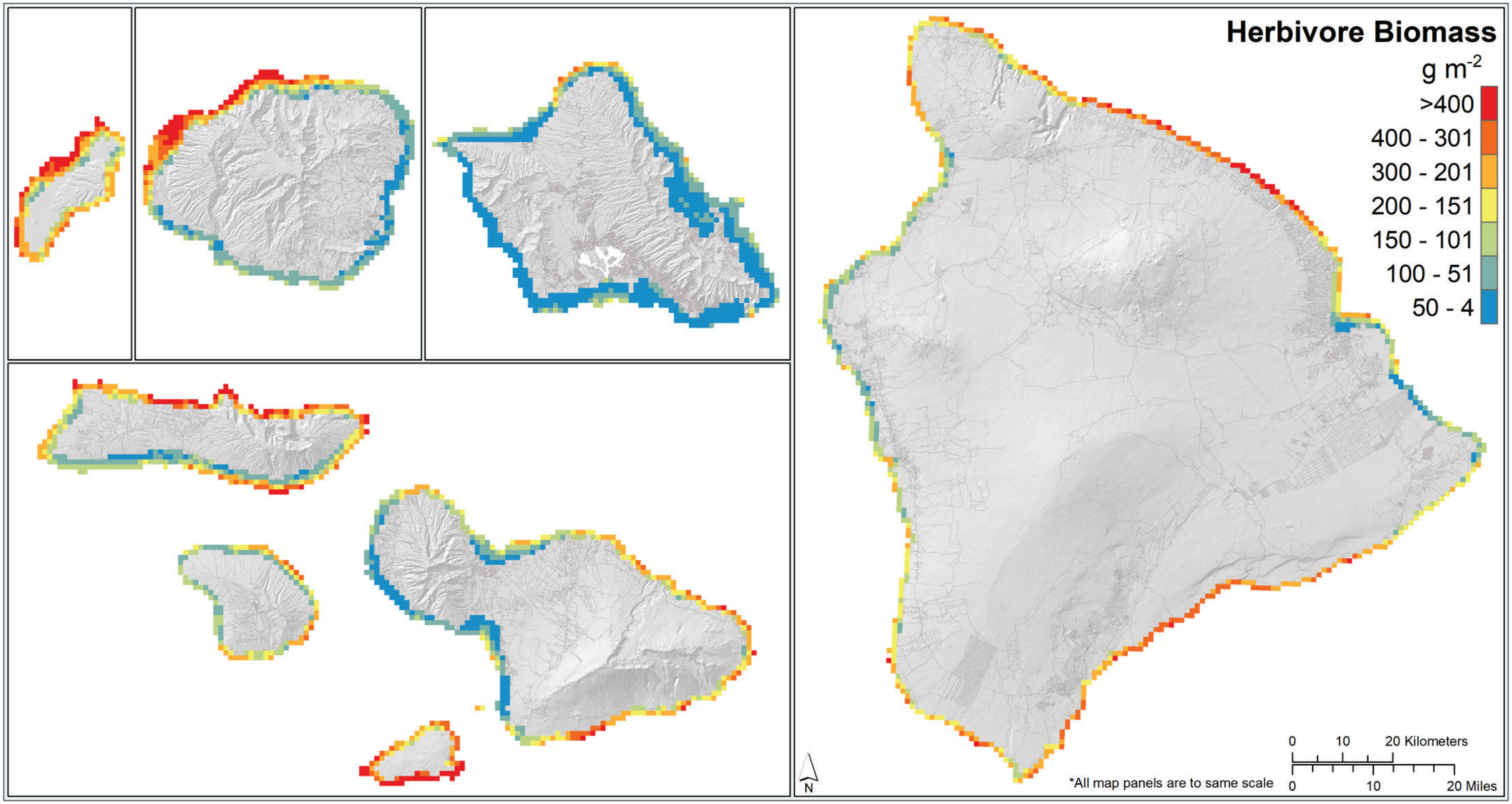
							predators tend to be k-selected species, biomass will be a better indicator of predator status.
Benthic cover							
1	% Coral cover	1	1	1	1	1	Coral is the primary ecosystem engineer for coral reef systems and therefore is the most direct measure of ecosystem state. Coral cover is also indicative of topographic complexity, habitat availability for other reef organisms, reef accretion, and diversity and abundance of coral species.
1	% Macroalgal cover	1	1	1	1	1	Macroalgae can reduce coral growth from direct competition for space and shading (McCook et al. 2001, Jompa & McCook 2002, Nugues & Bak 2006), increase microbial activity and disease transmission (Nugues et al. 2004, Smith et al. 2006, Weil et al. 2009), trap sediment that increases smothering (Birrell et al. 2005), reduce coral recruitment and settlement (Kuffner et al. 2006, Birrell et al. 2008, Vermeij et al. 2009), and further cause allelopathic effects (Kuffner et al. 2006, Rasher & Hay 2010).
0.625	Ratio calcified/fleshy cover	1	0.5	1	1	0.5	An alternative ratio has been proposed by Smith et al. (2016), which incorporates multiple benthic types into either a calcified state (dominated by corals and CCA), or a fleshy state (dominated by either turf or macroalgae). This metric was highly correlated with human impact gradients across the Pacific, and more closely relates

							to the mechanisms that determine resilience on reefs.
0.5	% Turf algal cover	1	0.5	0.5	0.5	0.5	Turf algae are a diverse assemblage of microalgae that are competitive and quickly occupy bare space, and coral settlement and survivorship can be negatively affected by turfs (McCook et al. 2001, Vermeij & Sandin 2008). However, turf can be a dominate feature of many nearshore reefs in Hawaiʻi (Jouffray et al. 2015, Donovan 2017), and therefore may not be an effective indicator of human impacts (Vroom & Braun 2010).
0.5	Ratio coral/macroalgal cover	1	0.5	0.5	0.5	0.5	Coral and macroalgal cover are commonly used as metrics to assess the state of coral reef systems, but this bimodal perspective may be lacking (Hughes et al. 2010, Mumby et al. 2013b, Jouffray et al. 2015). Some have used the ratio of coral and macroalgal cover as an indicator of a phase shift (Bruno et al. 2009), but this has been widely criticized for several reasons, such as a lack of reasoning for a cutoff or threshold that indicates moving towards or away from a coral dominated state (Hughes et al. 2010). Further, reefs may be better described by more than two states (Norström et al. 2009, Jouffray et al. 2015, Donovan 2017), so utilizing multiple metrics may be more useful than testing for bimodality.

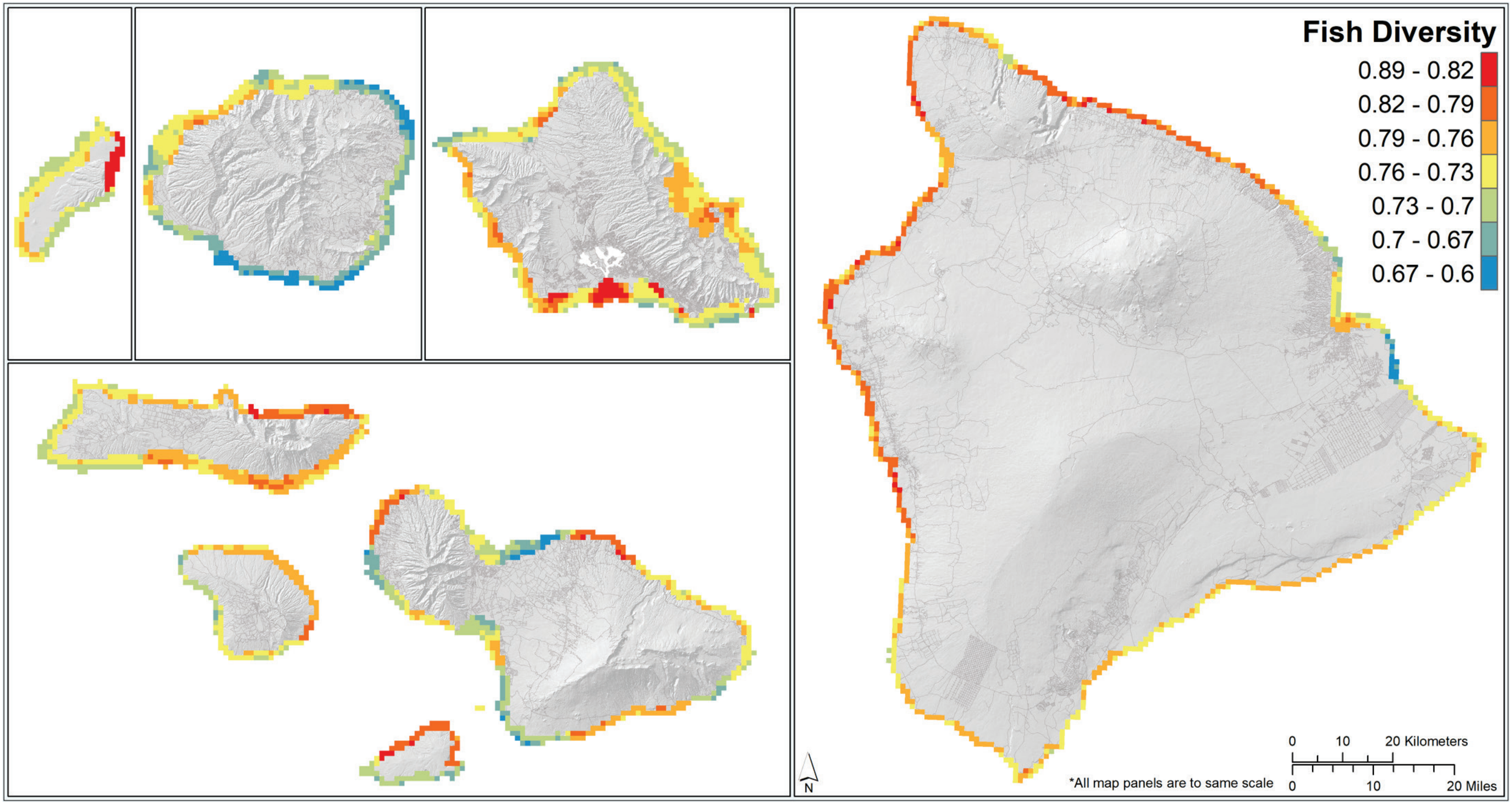
Indicator	Score from literature	CV score	Effect size score	Combined score	Correlations
Benthic cover					
% Coral cover	1	0.79	1.00	0.43	CM Ratio, Resistant Coral
% Macroalgal cover	1	0.69	0.11	0.37	
Ratio calcified/fleshy cover	0.75	0.62	0.09	0.29	
Ratio coral/macroalgal cover	0.5	0.69	0.80	0.00	
% Turf cover	0.5	0.91	0.41	0.00	
Biodiversity					
Fish species richness	0.75	0.92	0.19	0.27	
Non-native fish abundance	0.25	0.30	0.03	0.00	
Non-native algae cover	0	0.00	0.00	0.00	
Coral species richness	0.375	0.80	0.28	0.00	
Fish assemblage					
Total fish biomass	1	0.77	0.16	0.37	Total mSJ, Resource, Parrot > 25, Herb, Prime Spawner
Predator biomass	0.875	0.55	0.18	0.34	
Total fish abundance	0.875	0.85	0.19	0.32	
Predator abundance	0.75	0.77	0.19	0.29	
Total fish biomass (no sharks/jacks)	0.75	0.77	0.15	0.28	Total, Resource, Parrot > 25, Herbivore, Prime Spawner
Planktivore biomass	0.25	0.50	0.14	0.00	
Secondary consumer biomass	0.375	0.73	0.08	0.00	
Non-resource fish biomass	0.375	0.81	0.32	0.00	
Food fish					
Resource fish biomass	1	0.73	0.14	0.37	Total, Total mSJ, Parrot > 25, Herbivore, Prime Spawner
Prime spawner biomass	1	0.67	0.06	0.37	Total, Total mSJ, Resource, Parrot > 25
Size structure fish assemblage	1	0.93	0.12	0.35	
Herbivory					
Total Herbivore Biomass	1	0.73	0.15	0.37	Total, Total mSJ, Resource, Grazer, Parrot > 25
Biomass of parrotfish > 25 cm	0.875	0.69	0.14	0.33	Total, Total mSJ, Resource, Herbivore, Prime Spawner
Scraper Biomass	0.75	0.59	0.08	0.29	
Browser Biomass	0.625	0.60	0.09	0.25	
Grazer/Detritivore Biomass	0.625	0.69	0.11	0.24	Herbivore
Resilience					
% CCA cover	1	0.71	0.24	0.38	
% of coral resistant to bleaching	0.75	0.75	0.37	0.30	Coral cover
Corallivore fish abundance	0.625	0.77	0.09	0.23	

Appendix 3 – Indicator condition maps

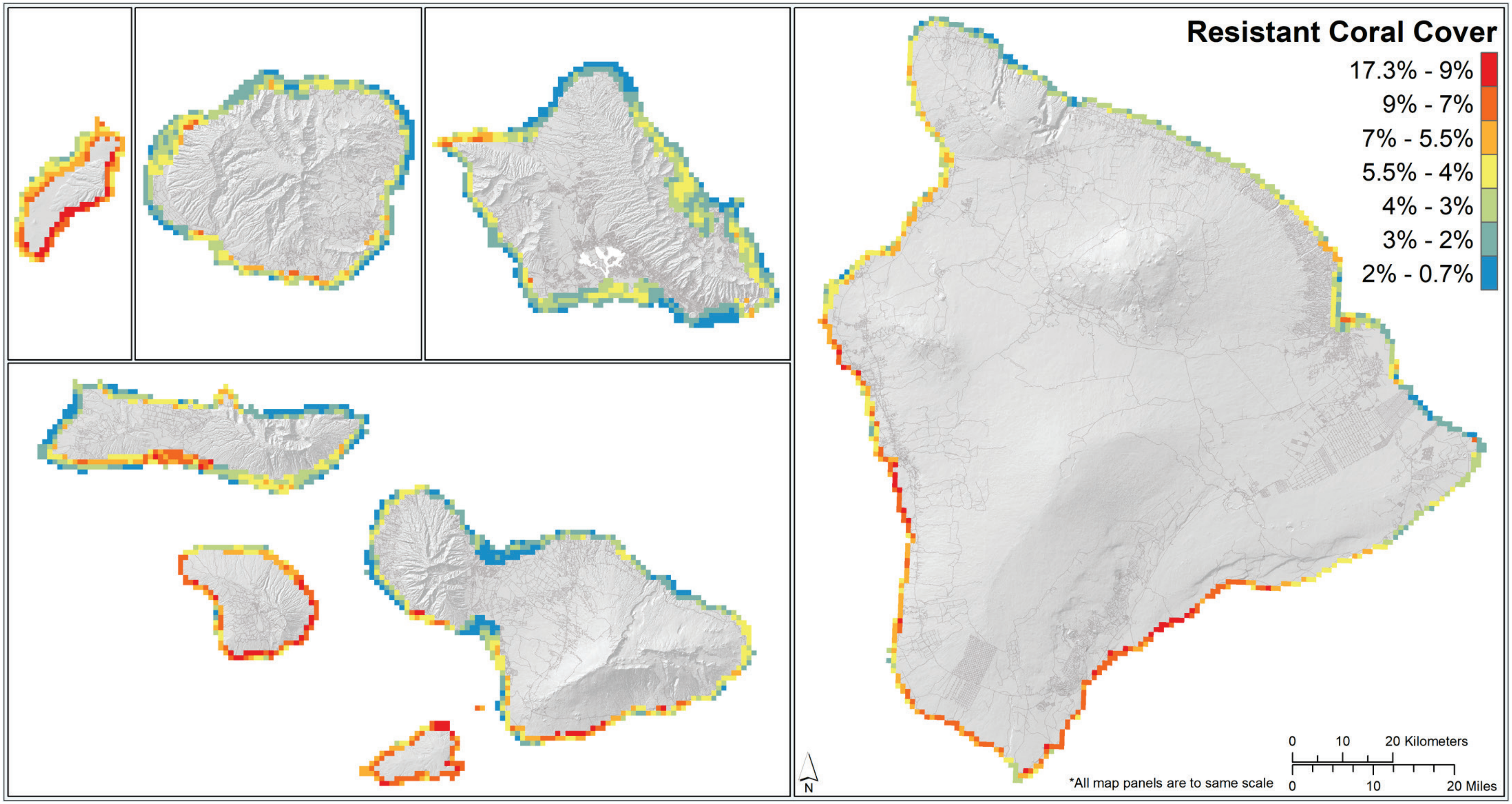


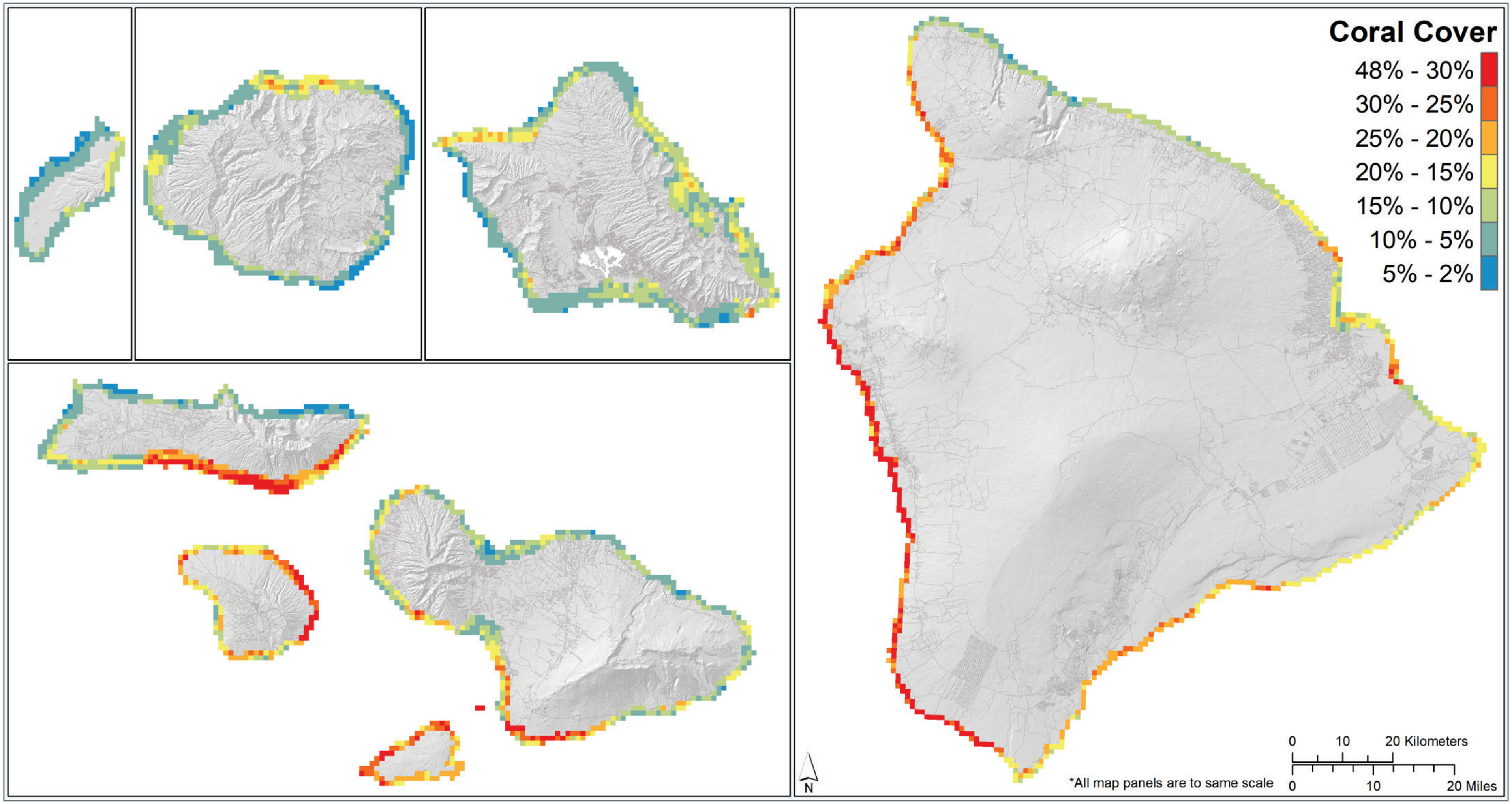


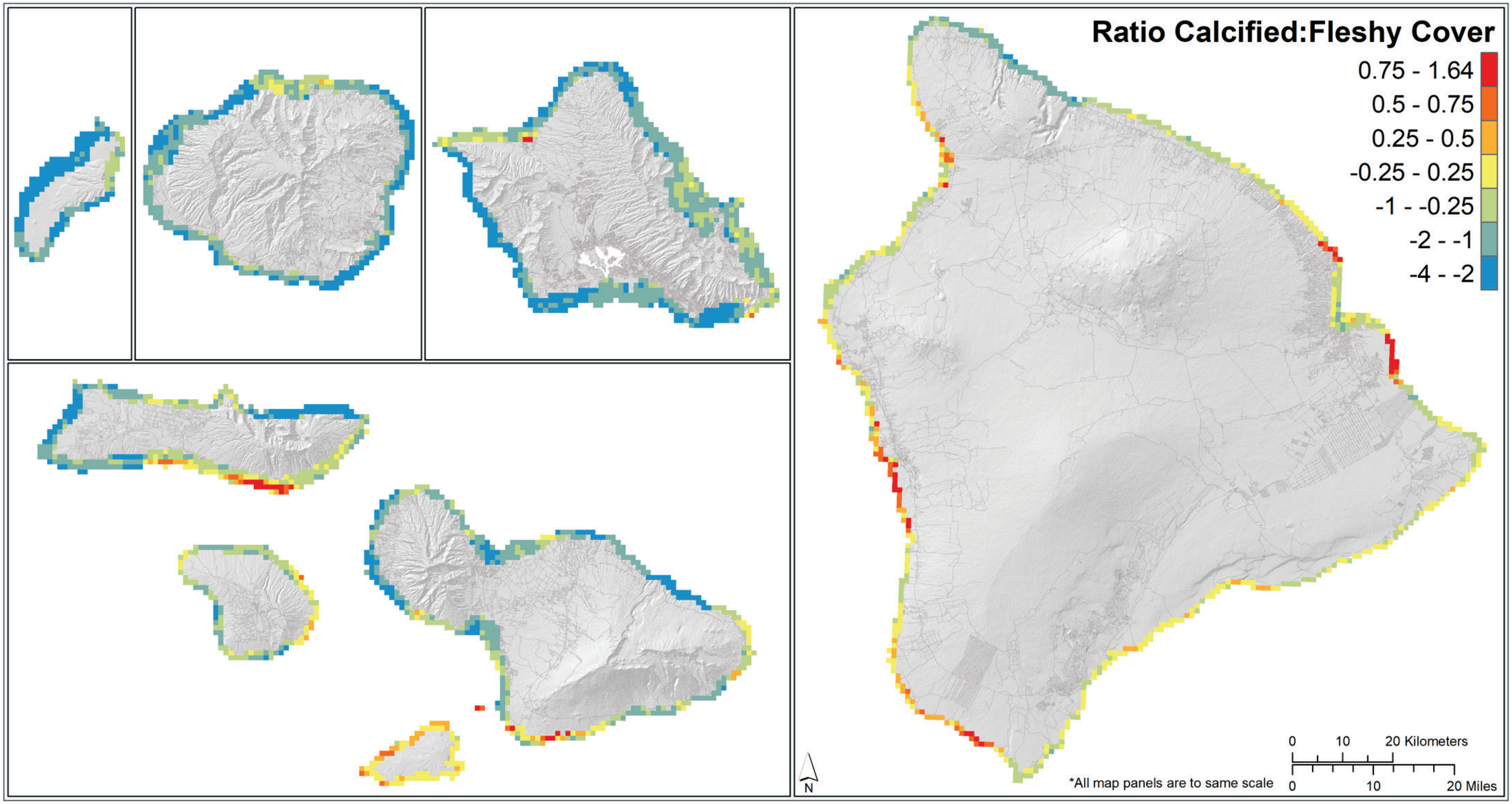
Herbivore Biomass
g m-2
>400
400 - 301
300 - 201
200 - 151
150 - 101
100 - 51
50 - 4
0 10 20 Kilometers
0 10 20 Miles
N
*All map panels are to same scale

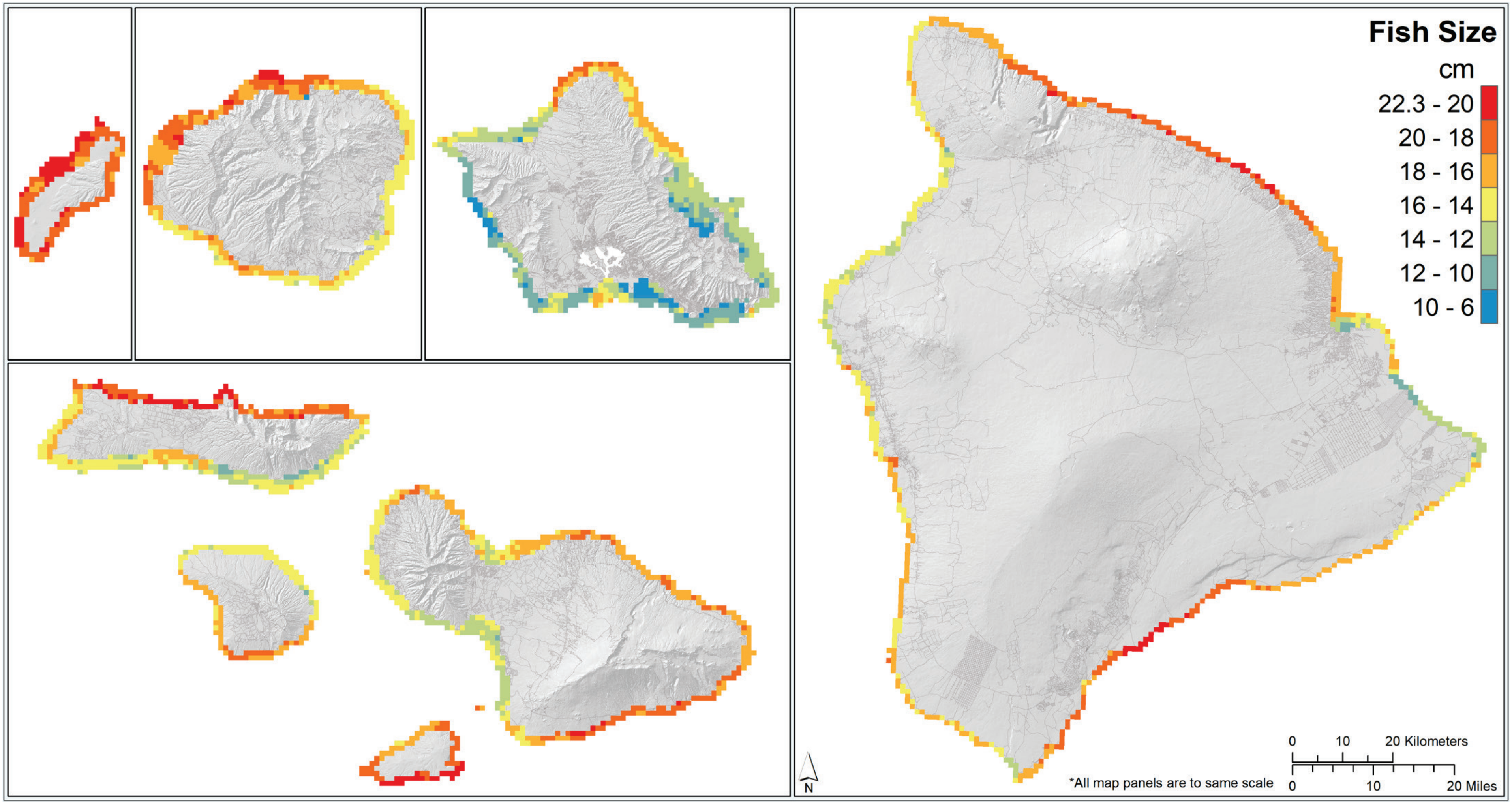


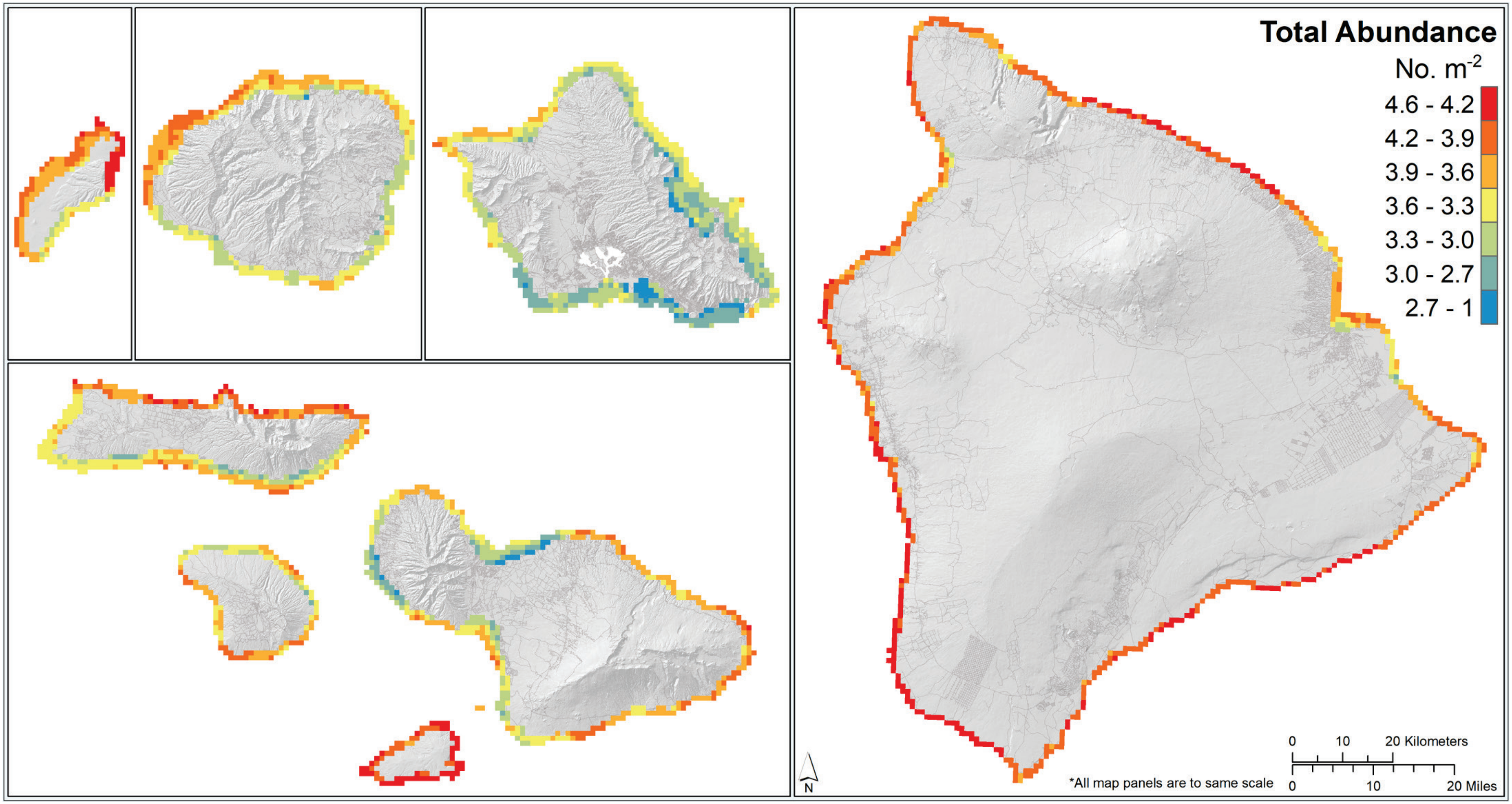
Fish Diversity
0.89 - 0.82
0.82 - 0.79
0.79 - 0.76
0.76 - 0.73
0.73 - 0.7
0.7 - 0.67
0.67 - 0.6
0
10
20 Kilometers
0
10
20 Miles
N
*All map panels are to same scale


Resistant Coral Cover
17.3% - 9%
9% - 7%
7% - 5.5%
5.5% - 4%
4% - 3%
3% - 2%
2% - 0.7%
N
*All map panels are to same scale
0 10 20 Kilometers
0 10 20 Miles

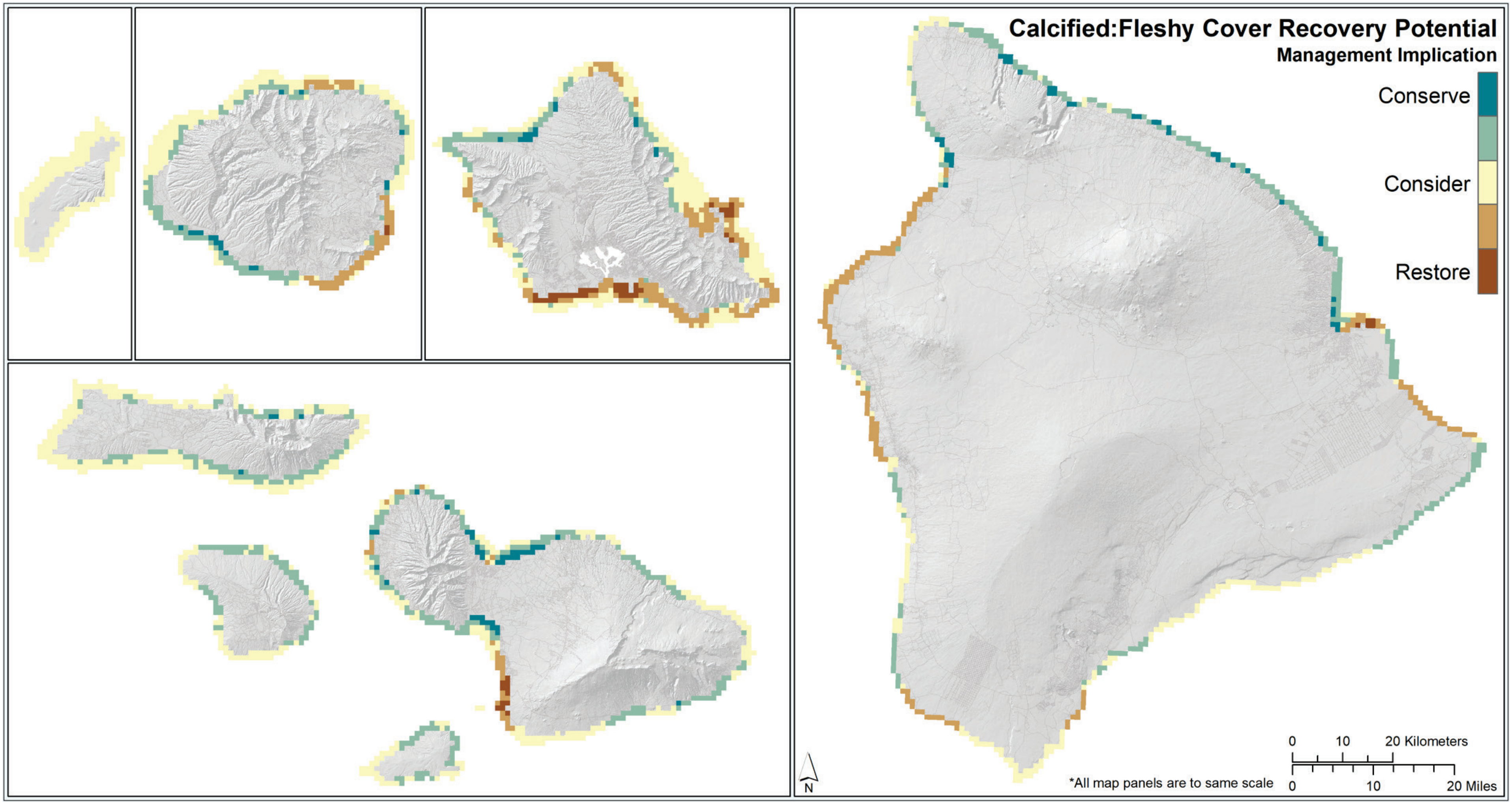

Coral Cover
48% - 30%
30% - 25%
25% - 20%
20% - 15%
15% - 10%
10% - 5%
5% - 2%
0 10 20 Kilometers
0 10 20 Miles
N
*All map panels are to same scale

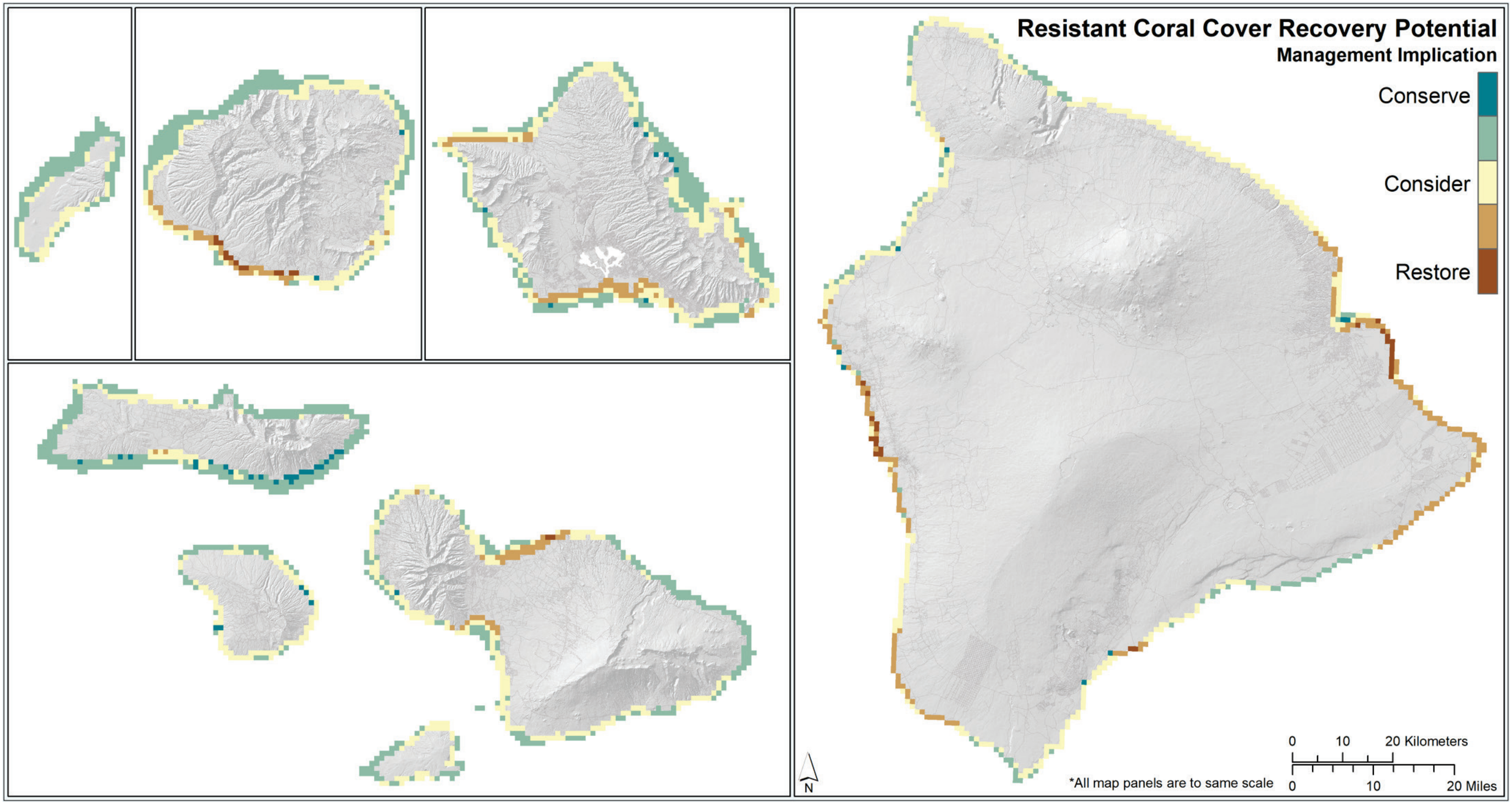

Ratio Calcified:Fleshy Cover
0.75 - 1.64
0.5 - 0.75
0.25 - 0.5
-0.25 - 0.25
-1 - -0.25
-2 - -1
-4 - -2
N
*All map panels are to same scale
0 10 20 Kilometers
0 10 20 Miles


Fish Size
cm
22.3 - 20
20 - 18
18 - 16
16 - 14
14 - 12
12 - 10
10 - 6
0
10
20 Kilometers
0
10
20 Miles
*All map panels are to same scale
N

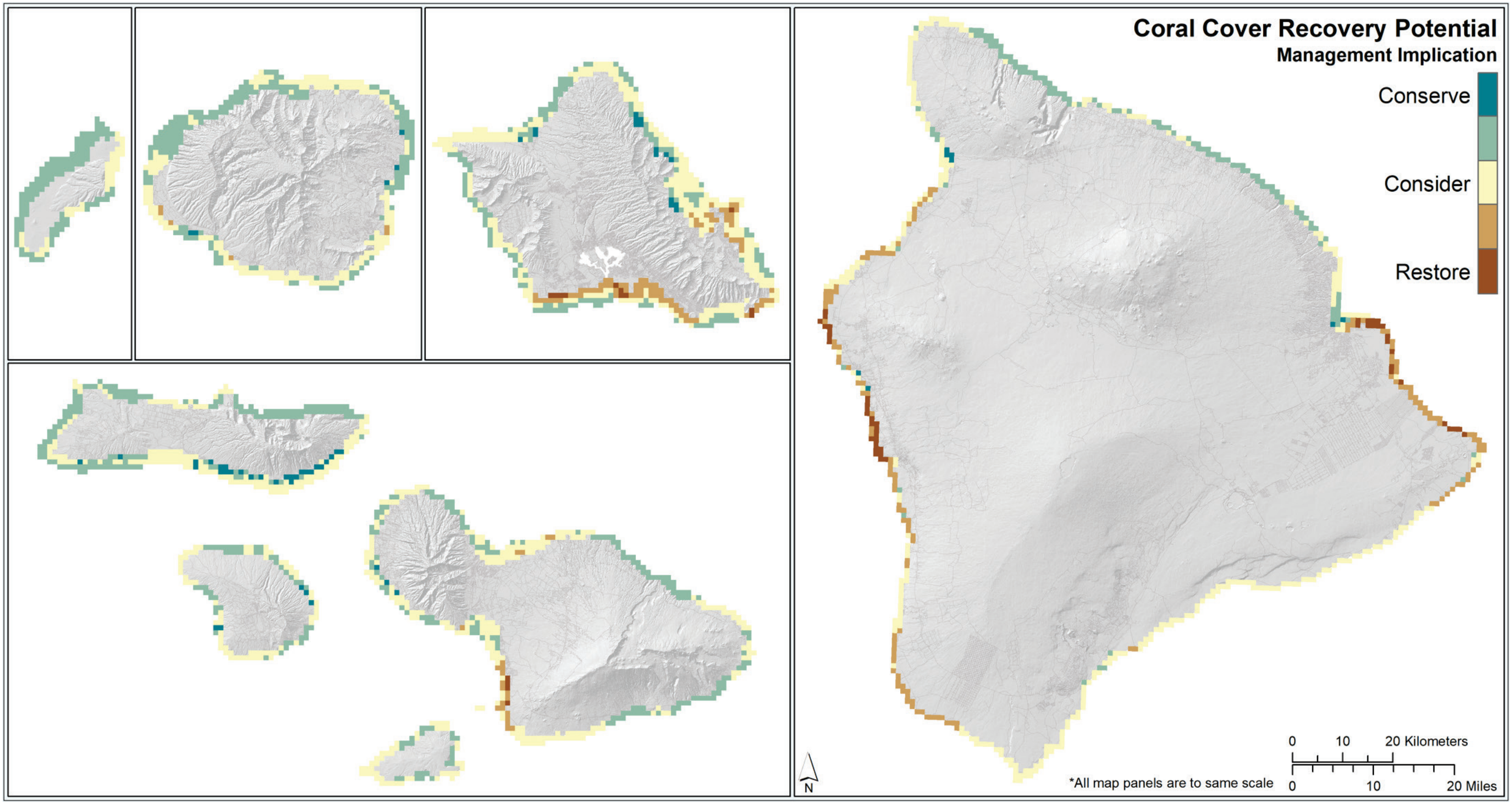

Total Abundance
No. m-2
4.6 - 4.2
4.2 - 3.9
3.9 - 3.6
3.6 - 3.3
3.3 - 3.0
3.0 - 2.7
2.7 - 1
0 10 20 Kilometers
0 10 20 Miles
*All map panels are to same scale
N

Appendix 4 – Recovery Potential

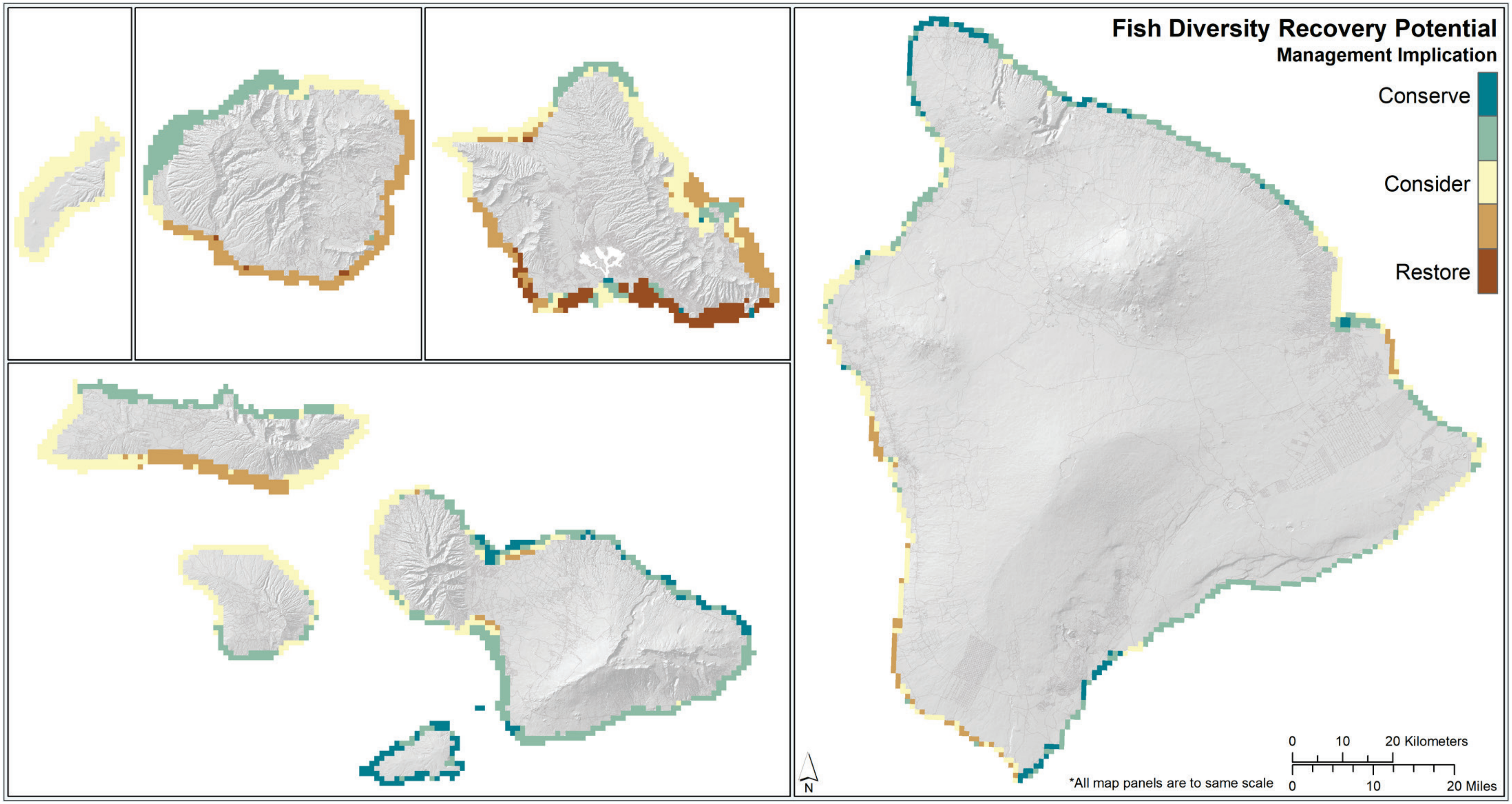


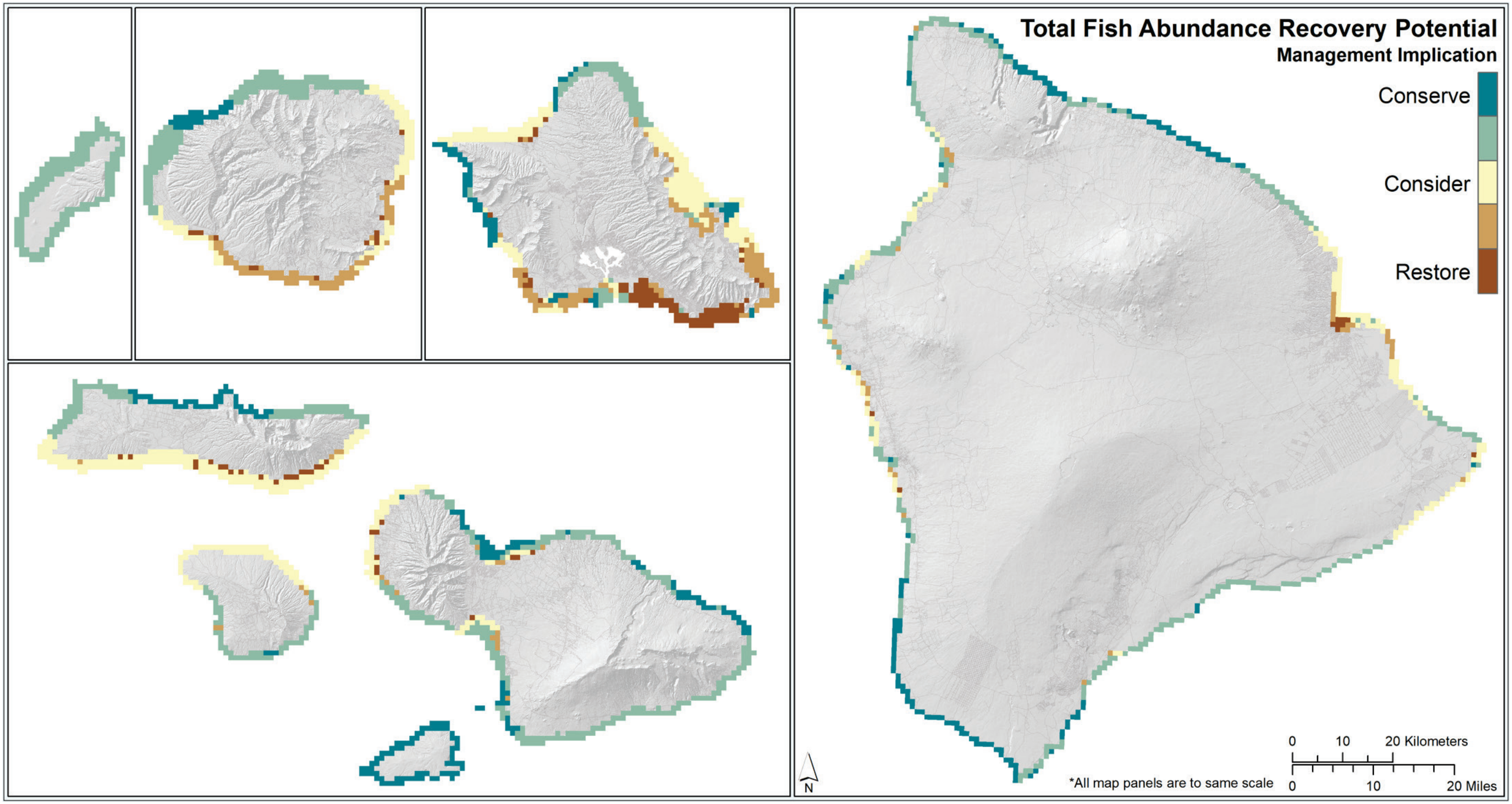


Resistant Coral Cover Recovery Potential
Management Implication
Conserve
Consider
Restore
N
*All map panels are to same scale
0
10
20 Kilometers
0
10
20 Miles

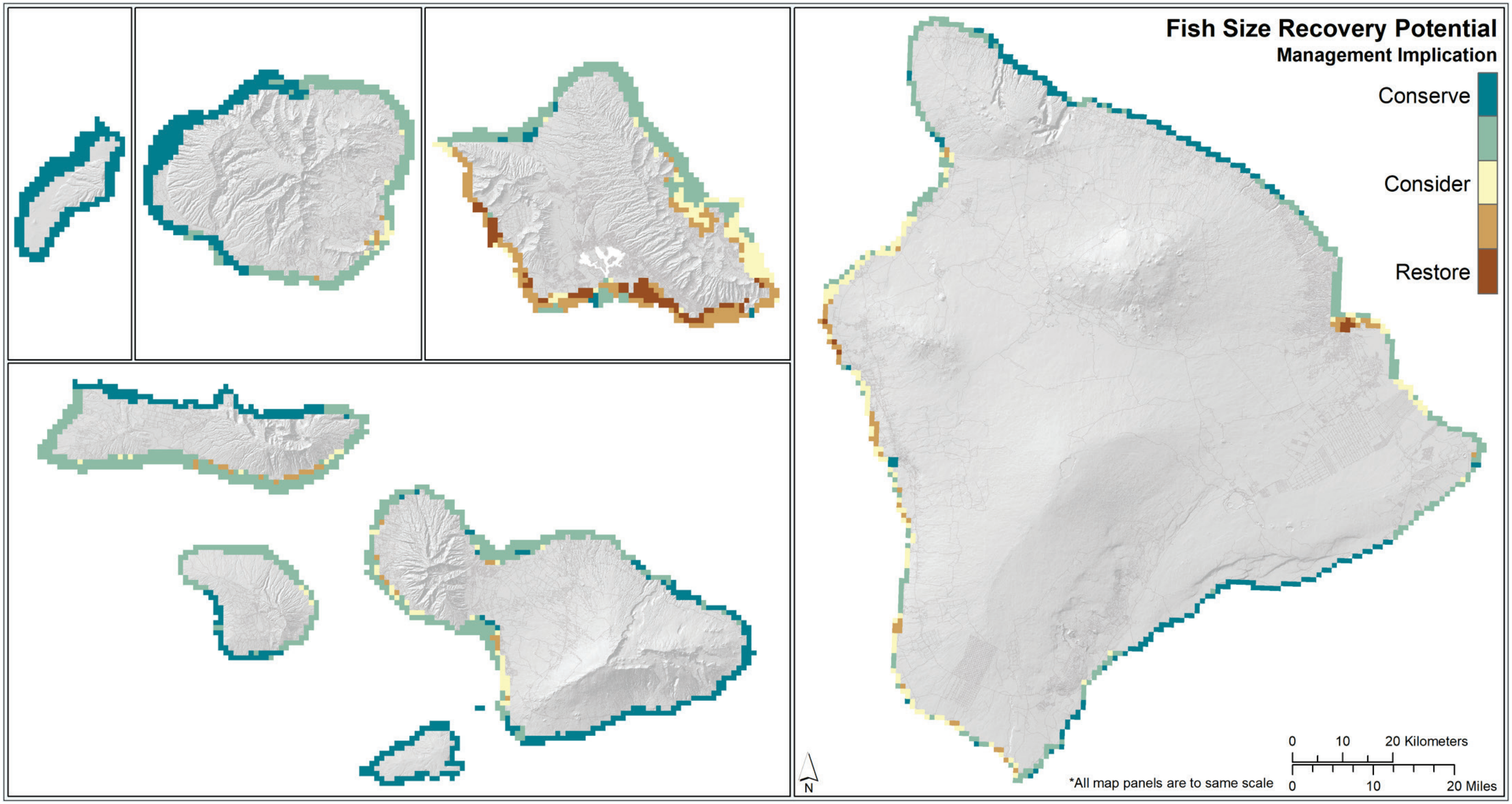


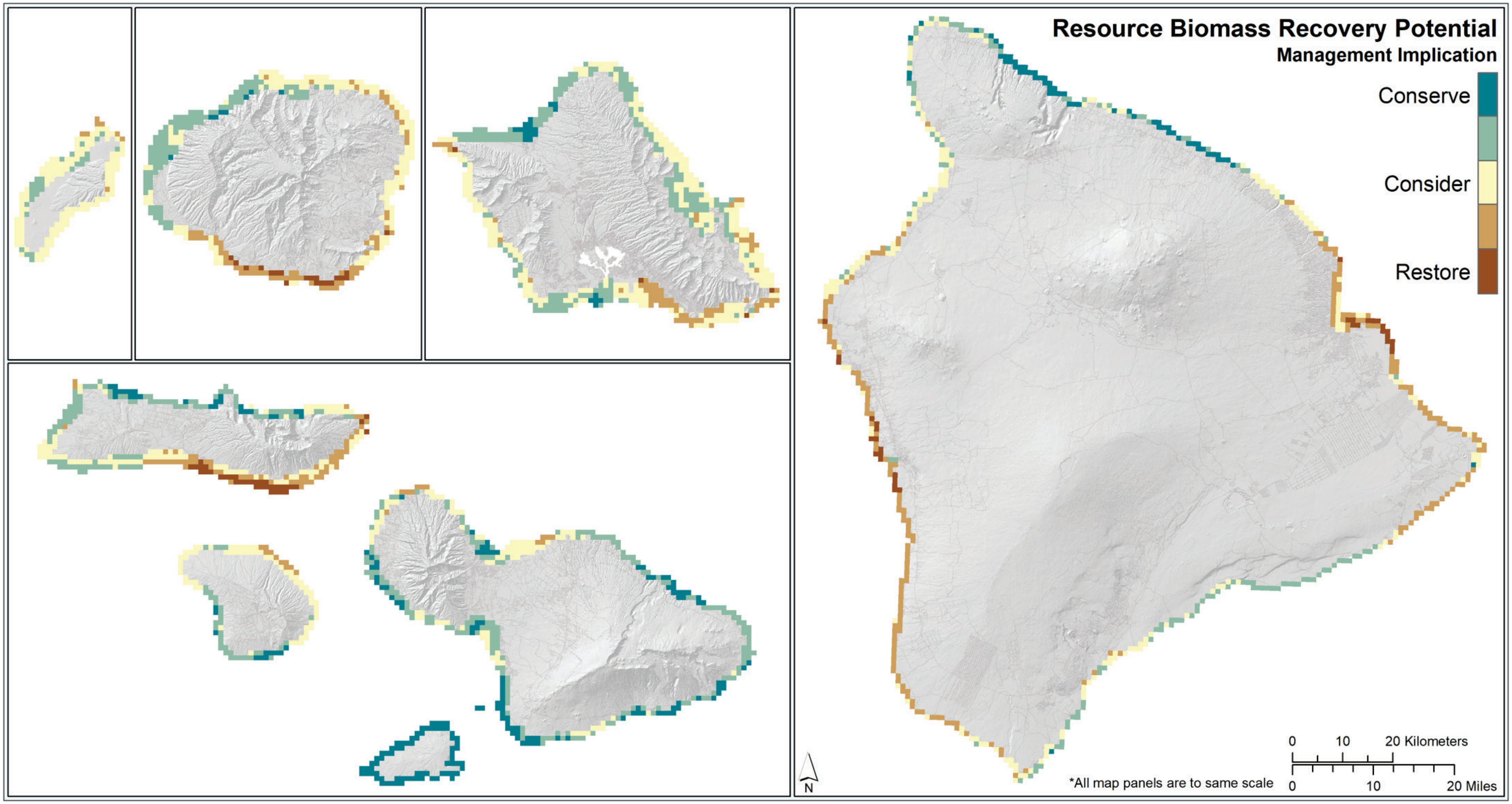
Coral Cover Recovery Potential
Management Implication
Conserve
Consider
Restore
0
10
20 Kilometers
0
10
20 Miles
*All map panels are to same scale
N


Fish Diversity Recovery Potential
Management Implication
Conserve
Consider
Restore
N
*All map panels are to same scale
0 10 20 Kilometers
0 10 20 Miles

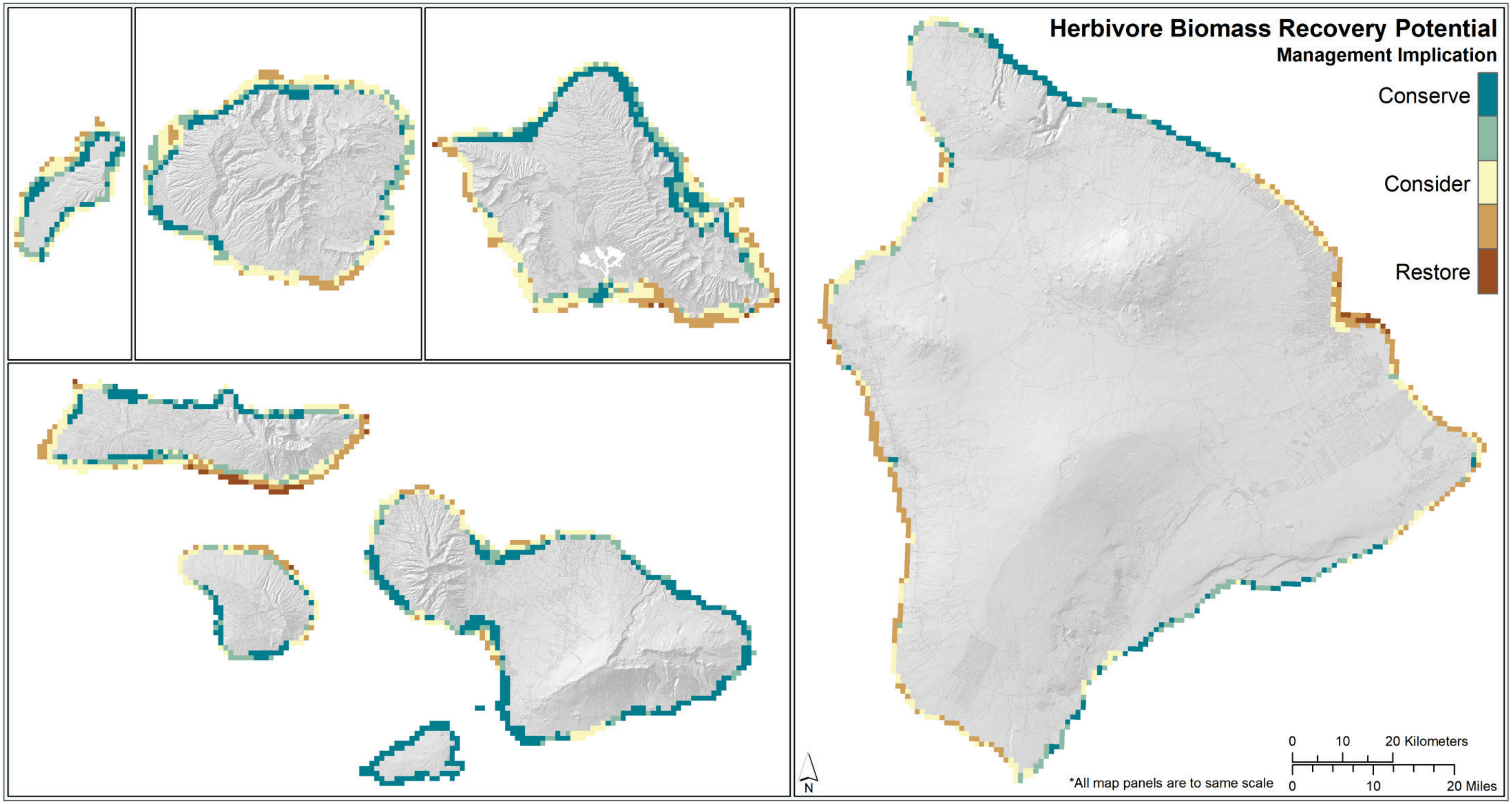


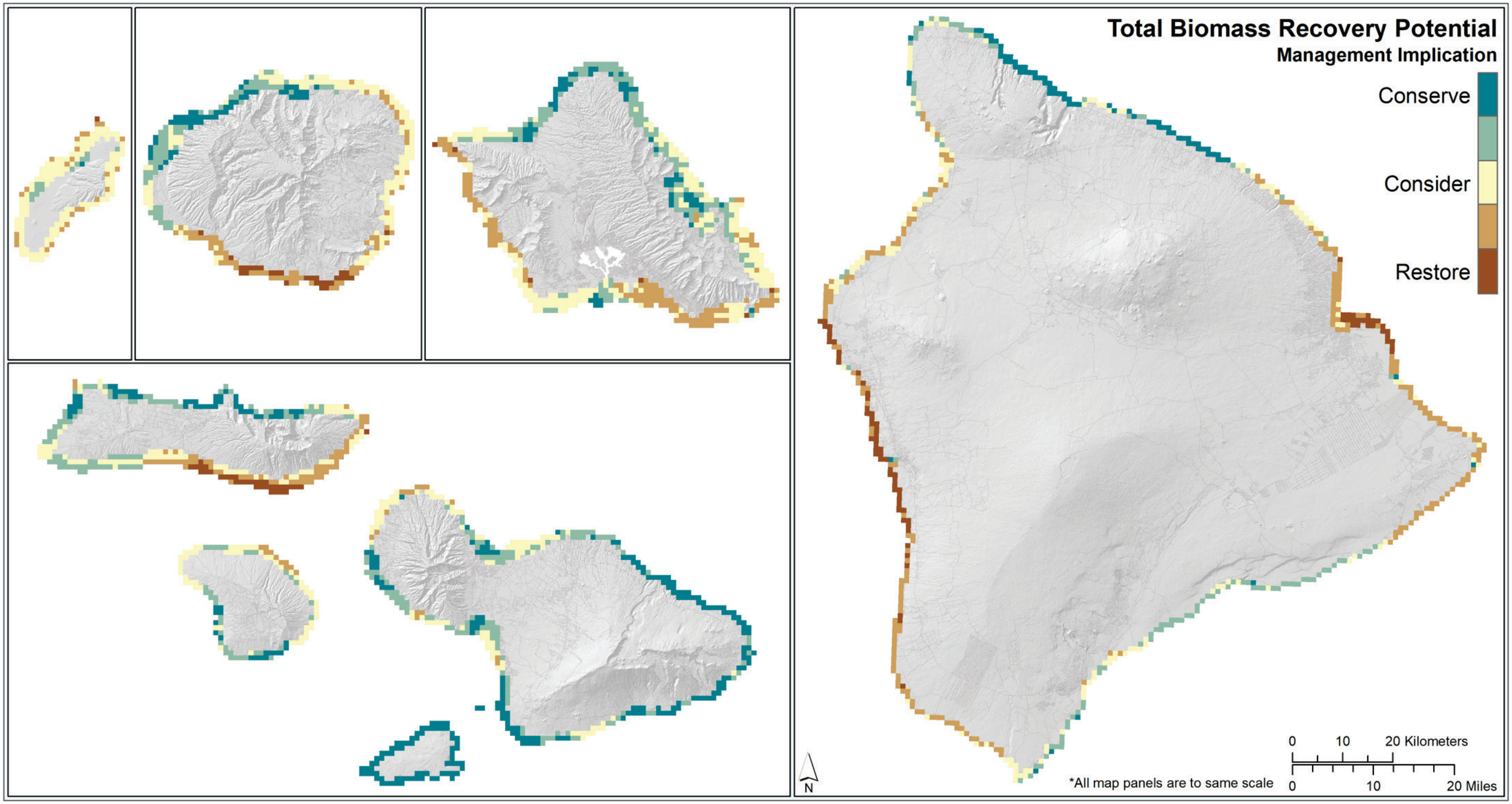
Total Fish Abundance Recovery Potential
Management Implication
Conserve
Consider
Restore
N
*All map panels are to same scale
0 10 20 Kilometers
0 10 20 Miles

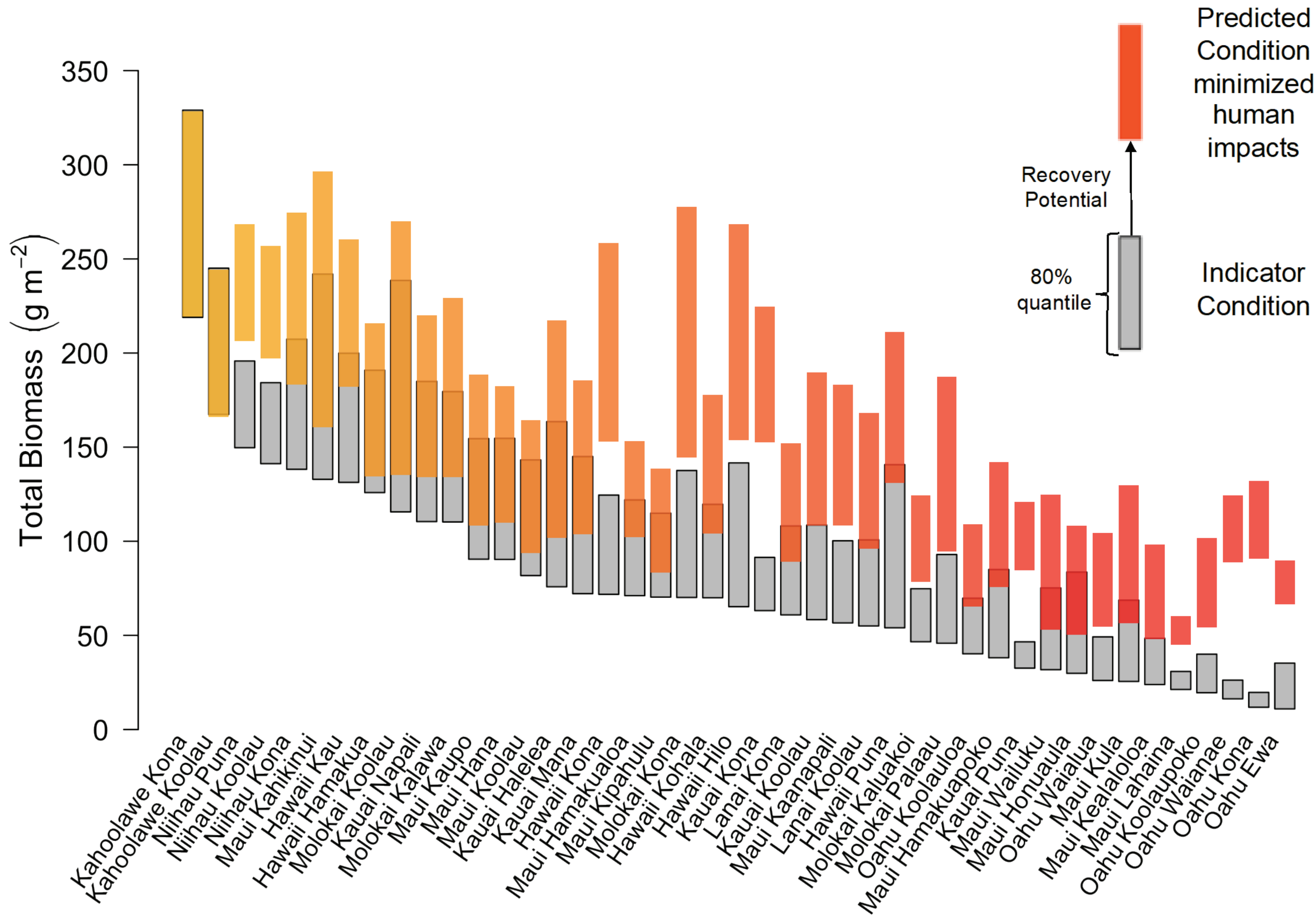

Fish Size Recovery Potential
Management Implication
Conserve
Consider
Restore
0 10 20 Kilometers
0 10 20 Miles
N
*All map panels are to same scale



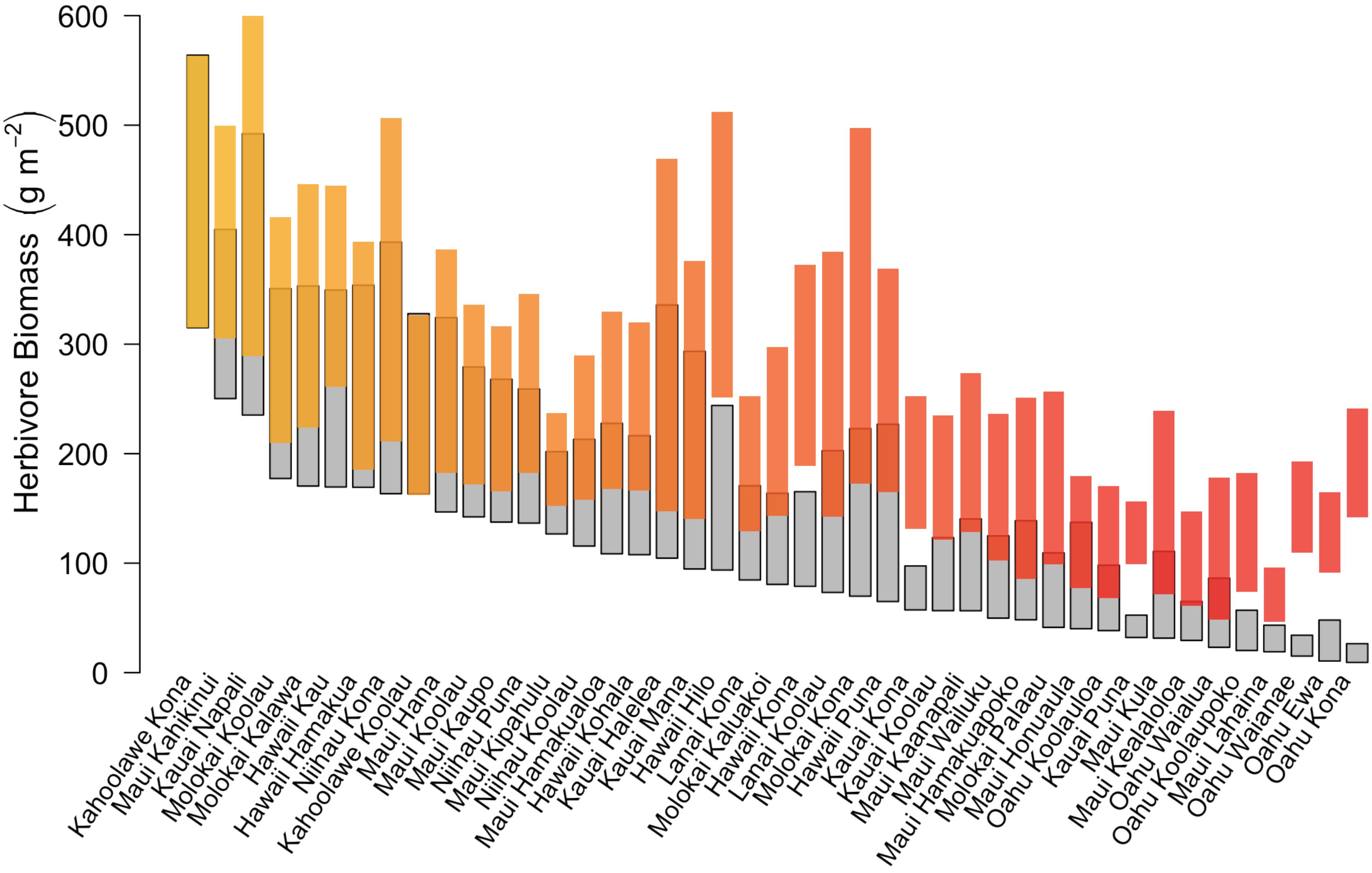
Resource Biomass Recovery Potential
Management Implication
Conserve
Consider
Restore
N
*All map panels are to same scale
0 10 20 Kilometers
0 10 20 Miles

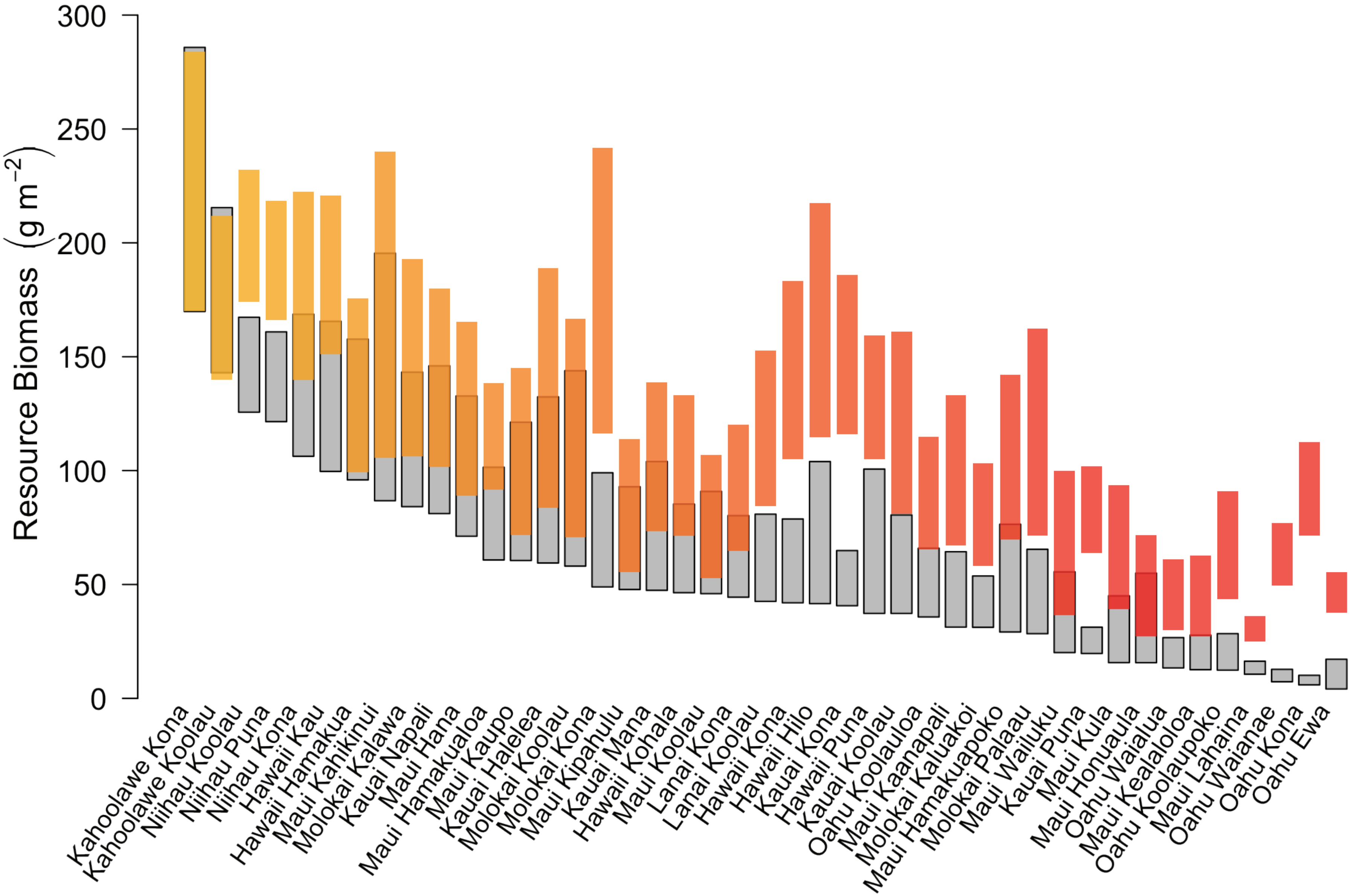

Herbivore Biomass Recovery Potential
Management Implication
Conserve
Consider
Restore
0 10 20 Kilometers
0 10 20 Miles
N
*All map panels are to same scale


Total Biomass Recovery Potential
Management Implication
Conserve
Consider
Restore
0 10 20 Kilometers
0 10 20 Miles
N
*All map panels are to same scale

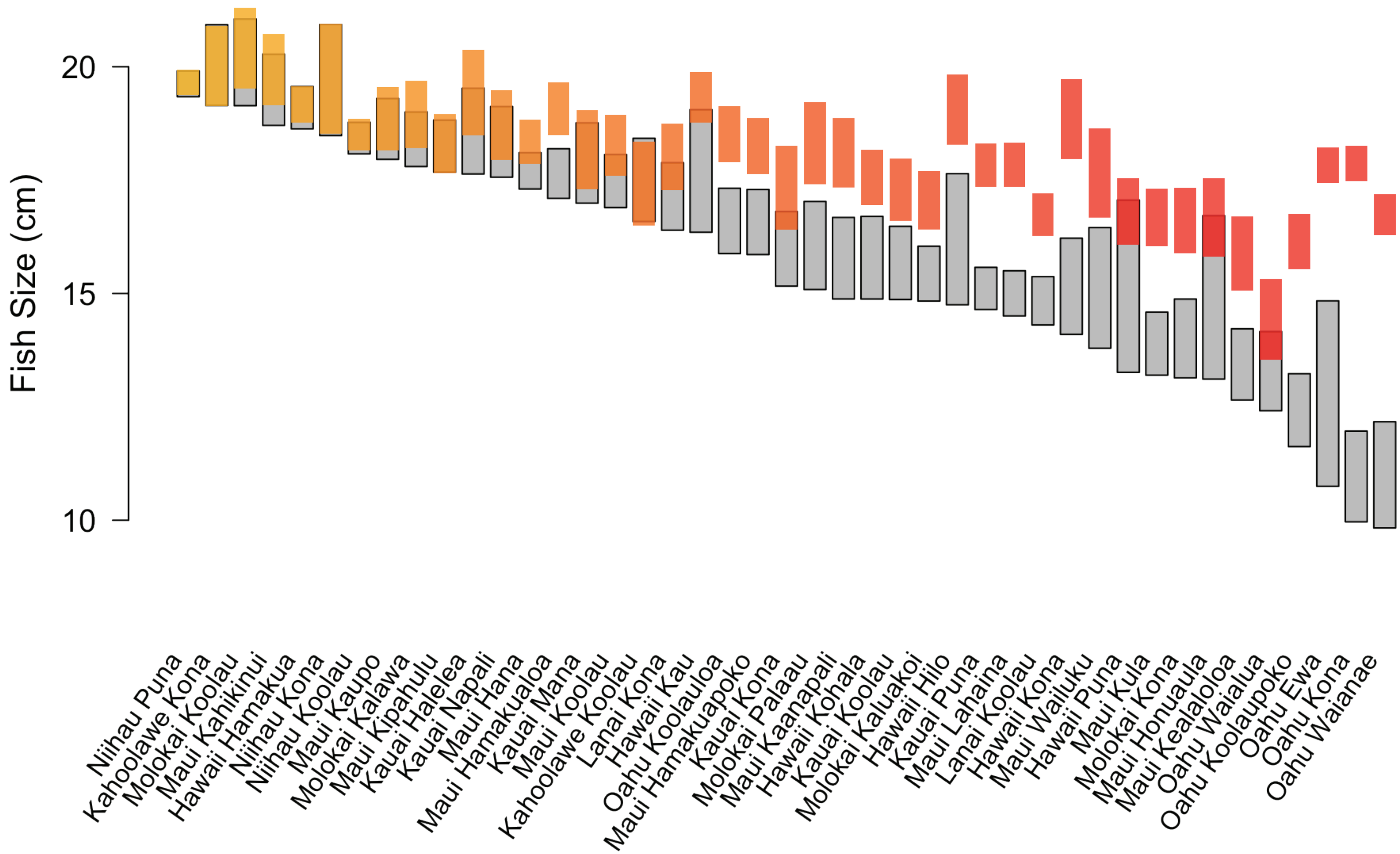


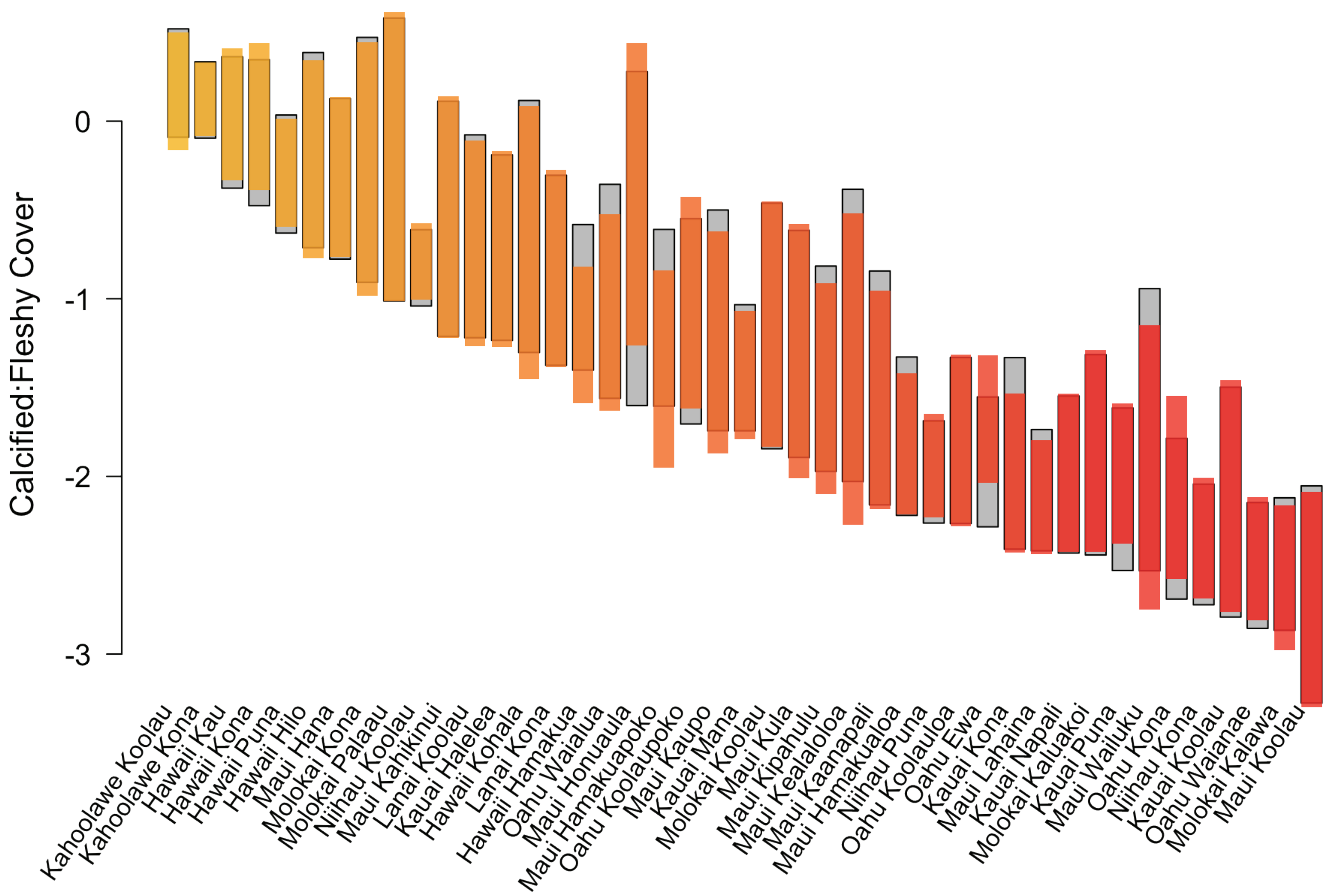
Total Biomass (g m^{-2})
350
300
250
200
150
100
50
0
Predicted Condition minimized human impacts
Recovery Potential
80% quantile
Indicator Condition
Kahoolawe Kona
Kahoolawe Koolau
Niihau Puna
Niihau Koolau
Niihau Kona
Maui Kahikinui
Hawaii Kau
Hawaii Hamakua
Molokai Koolau
Kauai Napali
Molokai Kalawa
Maui Kaupo
Maui Hana
Maui Koolau
Kauai Halelea
Kauai Mana
Hawaii Kona
Maui Hamakualoa
Maui Kipahulu
Molokai Kona
Hawaii Kohala
Hawaii Hilo
Kauai Kona
Lanai Kona
Kauai Koolau
Maui Kaanapali
Lanai Koolau
Hawaii Puna
Molokai Kaluakoi
Molokai Palaau
Oahu Koolauloa
Maui Hamakuapoko
Kauai Puna
Maui Wailuku
Oahu Honouaula
Oahu Waialua
Maui Kula
Maui Kealaloa
Maui Lahaina
Oahu Koolaupoko
Oahu Waianae
Oahu Kona
Oahu Ewa

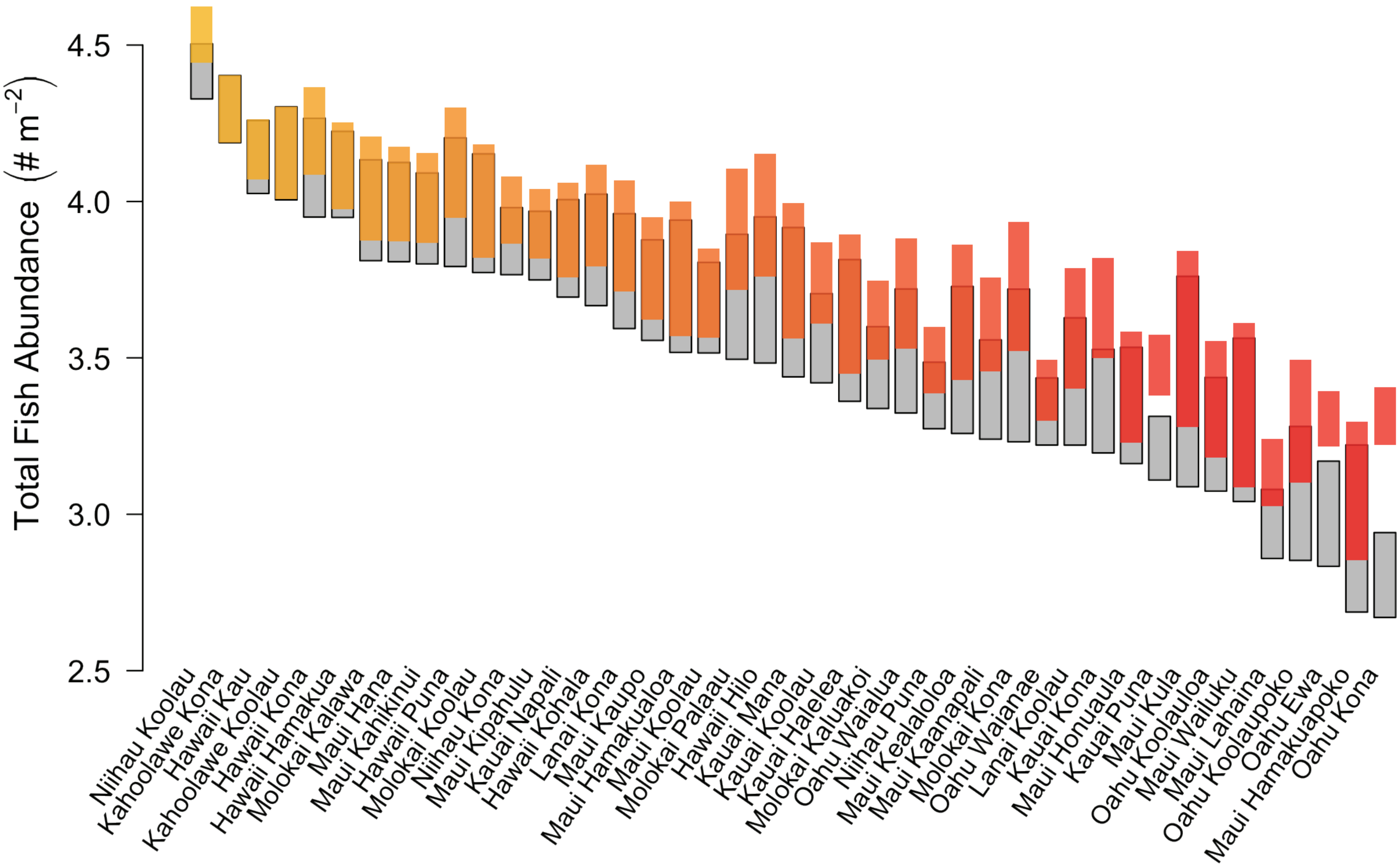

Herbivore Biomass (g m^-2)
600
500
400
300
200
100
0
Kahoolawe Kona
Maui Kahikinui
Kauai Napali
Molokai Koolau
Molokai Kalawa
Hawaii Kau
Hawaii Hamakua
Niihau Kona
Kahoolawe Koolau
Maui Hana
Maui Koolau
Maui Kaupo
Niihau Puna
Maui Kipahulu
Niihau Koolau
Maui Hamakualoa
Hawaii Kohala
Kauai Halelea
Kauai Mana
Hawaii Hilo
Lanai Kona
Molokai Kaluakoi
Hawaii Kona
Lanai Koolau
Molokai Kona
Hawaii Puna
Kauai Kona
Kauai Koolau
Maui Kaanapali
Maui Wailuku
Maui Hamakuapoko
Molokai Palaau
Maui Honuaula
Oahu Koolauloa
Kauai Puna
Maui Kula
Maui Kealaloloa
Oahu Waialua
Oahu Koolaupoko
Maui Lahaina
Oahu Waianae
Oahu Ewa
Oahu Kona

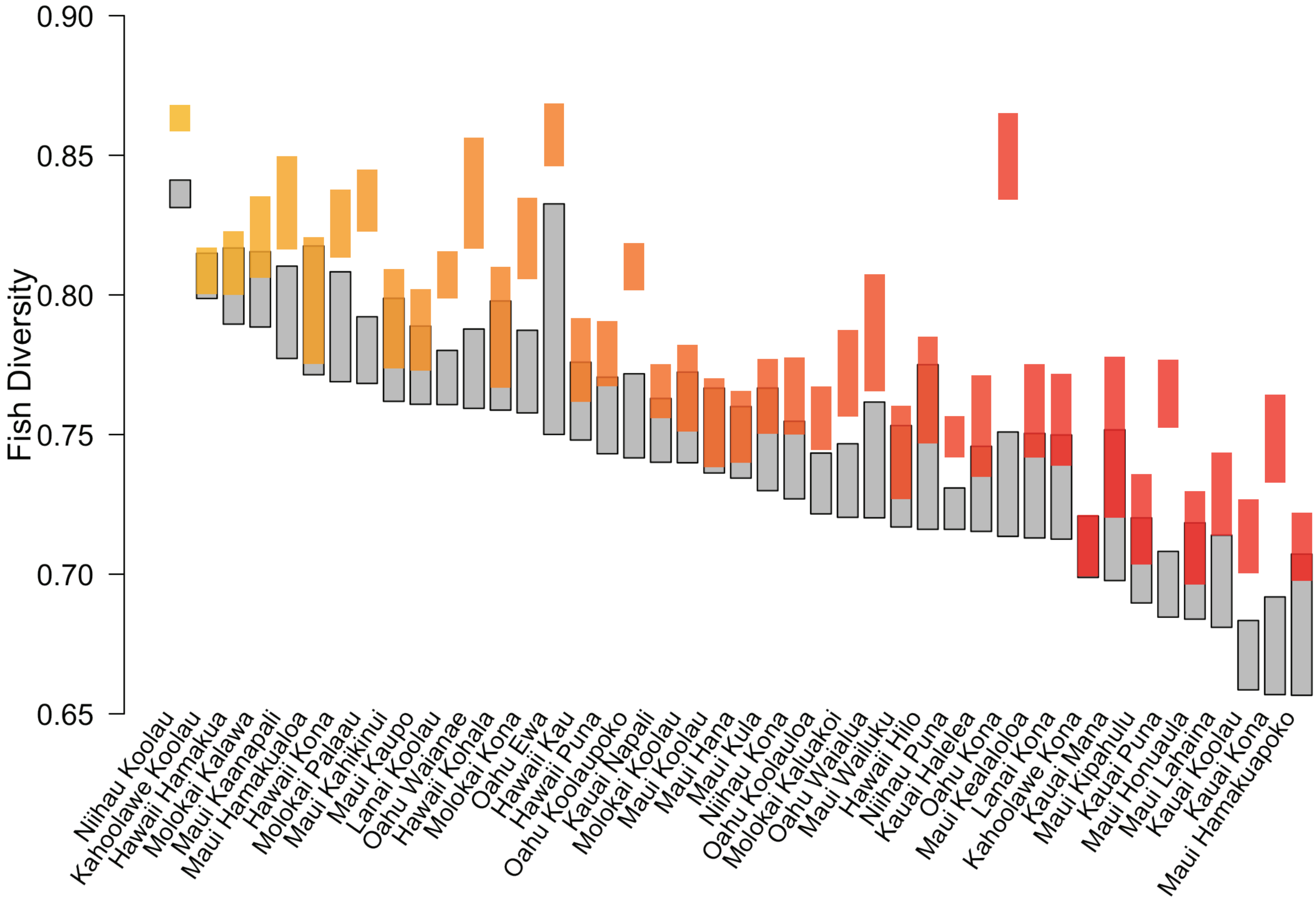


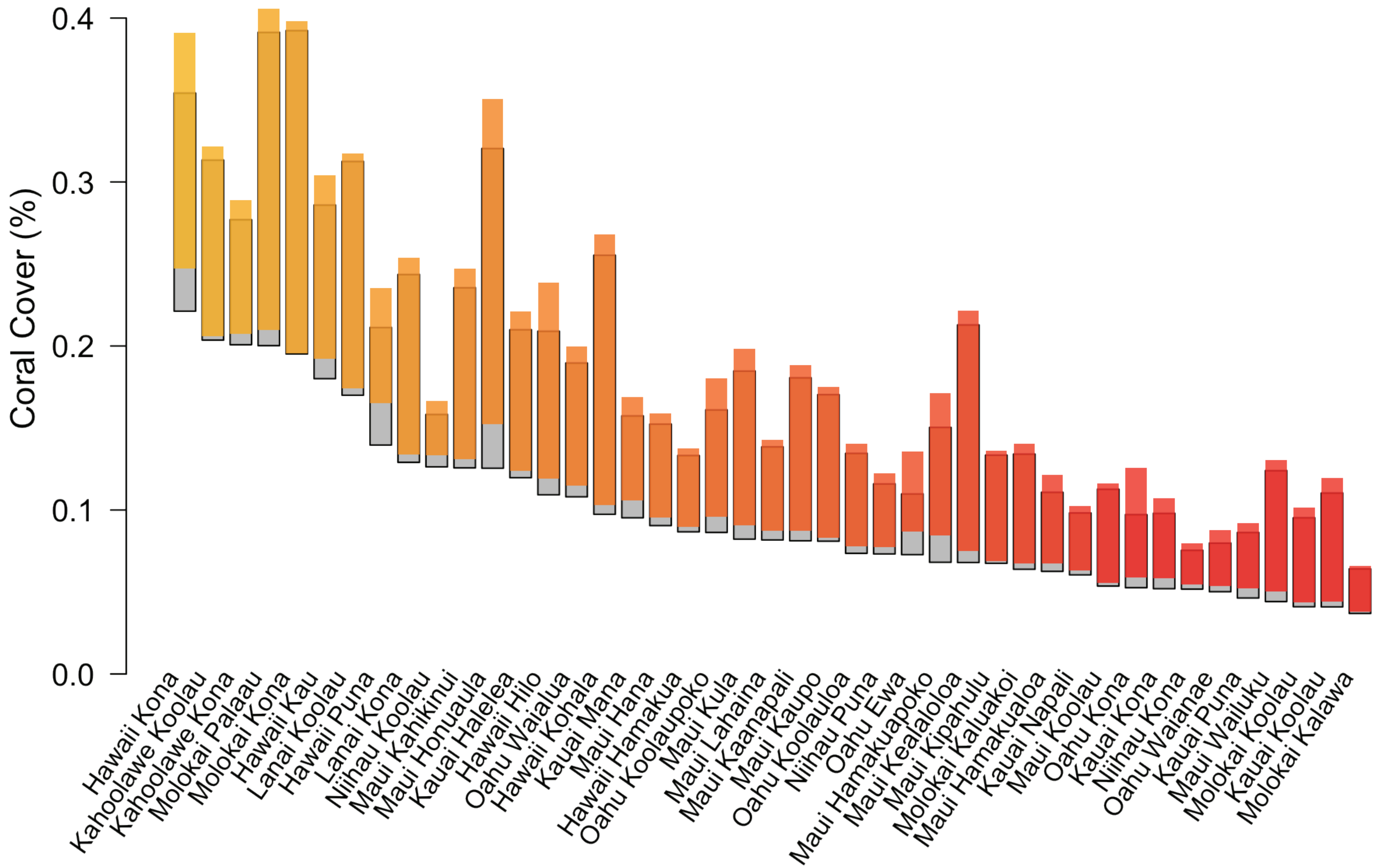
Resource Biomass (g m^-2)
300
250
200
150
100
50
0
Kahoolawe Kona
Kahoolawe Koolau
Niihau Koolau
Niihau Puna
Niihau Kona
Hawaii Kau
Hawaii Hamakua
Maui Kahikinui
Molokai Kalawa
Kauai Napali
Maui Hana
Maui Hamakualoa
Maui Kaupo
Kauai Halelea
Molokai Koolau
Molokai Kona
Maui Kipahulu
Kauai Mana
Hawaii Kohala
Maui Koolau
Lanai Kona
Lanai Koolau
Hawaii Kona
Hawaii Hilo
Kauai Kona
Hawaii Puna
Kauai Koolau
Oahu Koolauloa
Maui Kaanapali
Molokai Kaluakoi
Maui Hamakuapoko
Molokai Palaau
Maui Wailuku
Kauai Puna
Maui Kula
Maui Honuaula
Oahu Waialua
Maui Kealaloloa
Oahu Koolaupoko
Maui Lahaina
Oahu Waianae
Oahu Kona
Oahu Ewa

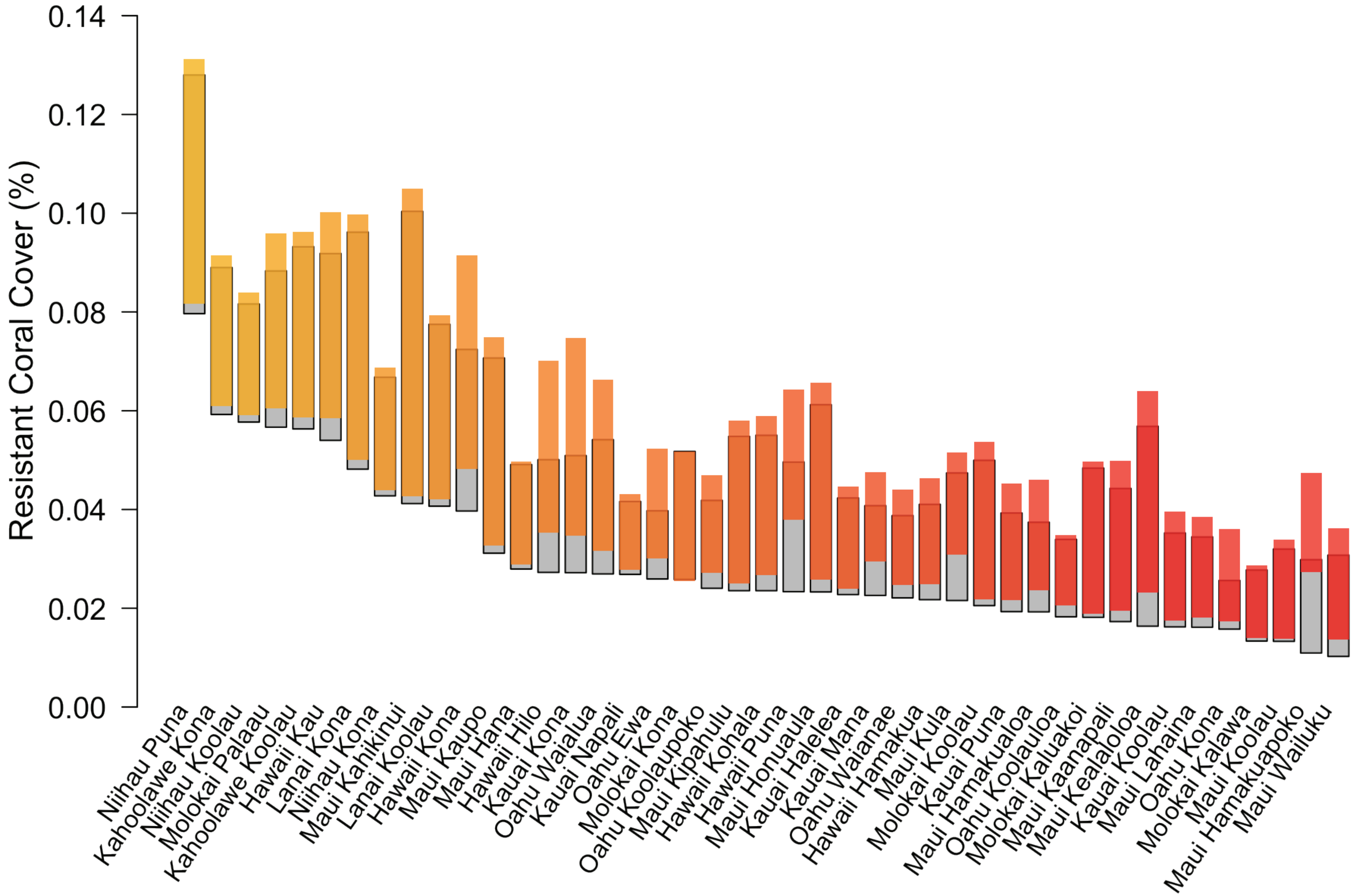

Fish Size (cm)
20
15
10
Niihau Puna
Kahoolawe Kona
Molokai Koolau
Maui Kahikinui
Hawaii Hamakua
Niihau Kona
Niihau Koolau
Maui Kaupo
Molokai Kalawa
Maui Kipahulu
Kauai Halelea
Kauai Napali
Maui Hana
Maui Hamakualoa
Kauai Mana
Maui Koolau
Kahoolawe Koolau
Lanai Kona
Hawaii Kau
Oahu Koolauloa
Maui Hamakuapoko
Kauai Kona
Molokai Palaau
Maui Kaanapali
Hawaii Kohala
Kauai Koolau
Molokai Kaluakoi
Hawaii Hilo
Kauai Puna
Maui Lahaina
Lanai Koolau
Hawaii Kona
Maui Wailuku
Hawaii Puna
Maui Kula
Molokai Kona
Maui Honuaula
Maui Kealaloloa
Oahu Waialua
Oahu Koolaupoko
Oahu Ewa
Oahu Kona
Oahu Waianae


Calcified:Fleshy Cover
0
-1
-2
-3
Kahoolawe Koolau
Kahoolawe Kona
Hawaii Kau
Hawaii Kona
Hawaii Puna
Hawaii Hilo
Maui Hana
Molokai Kona
Molokai Palaau
Niihau Koolau
Maui Kahikinui
Lanai Koolau
Kauai Halelea
Hawaii Kohala
Lanai Kona
Hawaii Hamakua
Oahu Waialua
Maui Honuaula
Maui Hamakuapoko
Oahu Koolaupoko
Maui Kaupo
Kauai Mana
Molokai Koolau
Maui Kula
Maui Kipahulu
Maui Kealaloloa
Maui Kaanapali
Maui Hamakualoa
Niihau Puna
Oahu Koolauloa
Oahu Ewa
Kauai Kona
Maui Lahaina
Kauai Napali
Molokai Kaluakoi
Kauai Puna
Maui Wailuku
Oahu Kona
Niihau Kona
Kauai Koolau
Oahu Waianae
Molokai Kalawa
Maui Koolau


Total Fish Abundance (# m^{-2})
4.5
4.0
3.5
3.0
2.5
Niihau Koolau
Kahoolawe Kona
Hawaii Kau
Kahoolawe Koolau
Hawaii Kona
Hawaii Hamakua
Molokai Kalawa
Maui Hana
Maui Kahikinui
Hawaii Puna
Molokai Koolau
Niihau Kona
Maui Kipahulu
Kauai Napali
Hawaii Kohala
Lanai Kona
Maui Kaupo
Maui Hamakualoa
Maui Koolau
Molokai Palaau
Hawaii Hilo
Kauai Mana
Kauai Koolau
Kauai Halelea
Molokai Kaluakoi
Oahu Waialua
Niihau Puna
Maui Kealaloloa
Maui Kaanapali
Molokai Kona
Oahu Waianae
Lanai Koolau
Kauai Kona
Maui Honuaula
Kauai Puna
Maui Kula
Oahu Koolauloa
Maui Wailuku
Maui Lahaina
Oahu Koolaupoko
Oahu Ewa
Maui Hamakuapoko
Oahu Kona


Fish Diversity
0.90
0.85
0.80
0.75
0.70
0.65
Niihau Koolau
Kahoolawe Koolau
Hawaii Hamakua
Molokai Kalawa
Maui Kaanapali
Maui Hamakualoa
Hawaii Kona
Molokai Palaau
Maui Kahikinui
Maui Kaupo
Lanai Koolau
Oahu Waianae
Hawaii Kohala
Molokai Kona
Oahu Ewa
Hawaii Kau
Hawaii Puna
Oahu Koolaupoko
Kauai Napali
Molokai Koolau
Maui Koolau
Maui Hana
Maui Kula
Niihau Kona
Oahu Koolauloa
Molokai Kaluakoi
Oahu Waialua
Maui Wailuku
Hawaii Hilo
Niihau Puna
Kauai Halelea
Oahu Kona
Maui Kealaloloa
Lanai Kona
Kahoolawe Kona
Kauai Mana
Maui Kipahulu
Kauai Puna
Maui Honuaula
Maui Lahaina
Kauai Koolau
Kauai Kona
Maui Hamakuapoko


Coral Cover (%)
0.4
0.3
0.2
0.1
0.0
Hawaii Kona
Kahoolawe Koolau
Kahoolawe Kona
Molokai Palaau
Molokai Kona
Hawaii Kau
Lanai Koolau
Hawaii Puna
Lanai Kona
Niihau Koolau
Maui Kahikinui
Maui Honuaula
Kauai Halelea
Hawaii Hilo
Oahu Waialua
Hawaii Kohala
Kauai Mana
Maui Hana
Hawaii Hamakua
Oahu Koolaupoko
Maui Kula
Maui Lahaina
Maui Kaanapali
Maui Kaupo
Oahu Koolauloa
Niihau Puna
Oahu Ewa
Maui Hamakuapoko
Maui Kealaloloa
Maui Kipahulu
Molokai Kaluakoi
Maui Hamakualoa
Kauai Napali
Maui Koolau
Oahu Kona
Kauai Kona
Niihau Kona
Oahu Waianae
Kauai Puna
Maui Wailuku
Molokai Koolau
Kauai Koolau
Molokai Kalawa


Resistant Coral Cover (%)
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
Niihau Puna
Kahoolawe Kona
Niihau Koolau
Molokai Palaau
Kahoolawe Koolau
Hawaii Kau
Lanai Kona
Niihau Kona
Maui Kahikinui
Lanai Koolau
Hawaii Kona
Maui Kaupo
Maui Hana
Hawaii Hilo
Kauai Kona
Oahu Waialua
Kauai Napali
Oahu Ewa
Molokai Kona
Oahu Koolaupoko
Maui Kipahulu
Hawaii Kohala
Hawaii Puna
Maui Honuaula
Kauai Halelea
Kauai Mana
Oahu Waianae
Hawaii Hamakua
Maui Kula
Molokai Koolau
Kauai Puna
Maui Hamakualoa
Oahu Koolauloa
Molokai Kaluakoi
Maui Kaanapali
Maui Kealaloloa
Kauai Koolau
Maui Lahaina
Oahu Kona
Molokai Kalawa
Maui Koolau
Maui Hamakuapoko
Maui Wailuku

Hawai'i Monitoring and Reporting Collaborative

HIMARC

National Park Service
NOAA
National Oceanic and Atmospheric Administration
U.S. Department of Commerce
The Nature Conservancy
Protecting nature. Preserving life.
DAR
Department of Land and Natural Resources
State of Hawaii
University of Hawai'i
Western Pacific Regional Fishery Management Council
Harold K.L. Castle Foundation
ASU Arizona State University
Center for Global Discovery and Conservation Science