A preliminary analysis examining linkages between reef fish assemblages and benthic habitat characteristics in Tutuila, American Samoa

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Introduction

Benthic habitats are known to play an important role in structuring the distribution and abundance of marine resources. In particular, many species of reef fish depend upon coral reefs for food, shelter, and habitat and are thus behaviorally influenced by the geomorphological structure of coral reefs (Sutton 1985). A number of studies have demonstrated correlations between fish assemblages and geomorphological benthic habitat structure (e.g., Friedlander and Parrish 1998, Richards et al. 2012, Williams et al. 2015,), however these relationships appear to vary widely across studies likely due to the different spatial scales being considered (Chitarro 2004).

Understanding the relationships that link biota with their underlying habitat is important to conservation practitioners and managers. For example, characterizing habitat-biota relationships can be useful in predictive mapping that can be used for identifying community responses to physical disturbance. It can also be used in assessing the relative importance of environmental features and provide insight as to which habitat areas should be prioritized for conservation purposes. From a fisheries management perspective, developing an improved understanding of linkages between fishes and their habitat is important for identifying essential fish habitat and habitat areas of particular concern and to reduce habitat-related uncertainty in stock assessments (National Marine Fisheries Service 2010). Furthermore, habitat-biota relationships are important for informing the design of stratified random surveys, whereby the environment (i.e., sampling domain) is partitioned into discreet sampling zones, and the amount of survey effort (e.g., the number of surveys) allocated to each sampling zone is based on its area and variance.

The latter is most related to the Coral Reef Ecosystem Division (CRED) and its implementation of the Pacific Reef Assessment and Monitoring Program. CRED uses a stratified random sampling design, but currently, only depth is used as an environmental correlate. Here, we derive several geomorphologic characteristics from multi-beam bathymetry data and investigate their relationship to different fish assemblage summary metrics collected from underwater visual census surveys. It is our hope to use this enhanced understanding of habitat-biota relationships to improve upon future reef fish sampling designs.

Methods

Geomorphologic Benthic Habitat Characteristics

A mosaic of gridded multibeam bathymetry and bathymetry derived from multispectral IKONOS satellite imagery of Tutuila Island, American Samoa (NOAA CRED 2009) was initially examined to derive the geomorphologic benthic habitat characteristics. The accuracy of the remotely-sensed bathymetry is greatly influenced by several factors all related to imagery: including the sensing environments (e.g. solar elevation and azimuth, platform height), atmospheric condition (e.g., absorption and scattering), water surface conditions (e.g. roughness, waves and currents), subsurface water conditions (scattering), and substrate reflectance properties (Gao 2009). Although Hogrefe et al. (2008) reported that the derived bathymetry is reasonably correlated to control data and effective at detecting subtle terrain features, it was observed that the noise introduced by these image properties are more prominent in the geomorphologic benthic habitat characteristics. Therefore, the bathymetry derived from multispectral IKONOS satellite imagery was excluded from our analysis here.

Thus, using only gridded multibeam bathymetry, we derived a series of benthic geomorphology variables for the nearshore environment of Tutuila Island, American Samoa (NOAA CRED 2006) using the open source GIS software, System for Automated Geoscientific Analysis (SAGA) version 2.1.4 (Conrad et al., 2015). A total of seven geomorphology variables were derived for this study: depth, slope, aspect, profile curvature, real surface area, rugosity, and terrain surface convexity. Profile curvature was derived with the “Slope, Aspect, Curvature tool” using the nine parameter 2^{nd} order polynomial method (Zevenbergen and Thorne 1987). Profile curvature is parallel to the direction of the maximum slope indicating whether the surface is convex or concave. Real surface area (Grohmann et al. 2009) was derived using “Real Surface Area tool”, which was then also used to calculate rugosity, a measure of roughness, derived by dividing real surface area by the geometric surface area. Lastly, terrain surface convexity is measured as the percentage of convex-upward cells within a constant radius of ten cells (Iwahashi and Pike 2007). Watkins (2015) describes further details on calculating each of these benthic geomorphology variables.

For each of the benthic geomorphology variables described above, site-specific values were then extracted for each fish survey location in Tutuila Island using ESRI’s ArcToolbox. In addition, in order to include the characteristics of the surroundings of each survey location, and to account for positional uncertainties of survey locations, geomorphology values were averaged across all cells with available data within radius of 30, 50, and 100m from the fish survey site. Thus, each of the seven benthic geomorphology variables described above, actually corresponds to four separate datasets: one that is based on the site-specific value for each fish survey, and three that are based on spatial averaging buffers that average across all cells within 30, 50, and 100m from the survey site. This allowed us to investigate the influence of spatial scale on habitat-fish correlations.

Fish Variables

Fish data were collected around Tutuila, American Samoa in 2010, 2012, and 2015 using identical methods as part of the Reef Assessment and Monitoring Program. Before each field season, fish survey sites are randomly selected at hard-bottom depths between 0 and 30 m, with effort (i.e., the number of survey sites) allocated proportionally to the amount of reef area found at three depth strata (0 – 6 m; 6 – 18 m; and 18 – 30 m). At each survey site, paired divers collect replicate data on fish sizes and counts using a stationary point count (SPC) method. The survey consists of: (i) a five-minute enumeration period when divers record all fish species that pass through a visually estimated cylinder of 7.5 m radius and (ii) a tallying period when divers record all sizes and counts of all fish species listed during the enumeration period. For more information of fish survey methodology, details are available at Ayotte et al. 2011. Count and size data can then be converted to fish biomass (g m^{-2}). Fish biomass are then summarized at an island-level spatial scale by first pooling across sites within strata, and then summing across strata weighted by reef area. For this project, we used a total of nine fish biomass metrics, including four trophic groups (primary consumers, secondary consumers, planktivores, piscivores), three size classes (0 – 20 cm; 20 – 50 cm; and 50+ cm), as well as parrotfishes and total fish biomass. All fish biomass indicators are deemed to be priority indicators by the NOAA National Coral Reef Monitoring Plan (NOAA Coral Program 2014).

Design Performance:

To reveal trends, all possible paired datasets of fish biomass and geomorphological characteristics were displayed in separate scatterplots. For each scatterplot, we calculate the mean biomass of all fish surveys in the dataset, and use local polynomial regression fitting (*loess,* α = 1.5) to fit a smoothed curve and 95% confidence intervals (estimated using standard error) to the data. The *loess* model works by fitting a low-degree polynomial using weighted least squares, meaning that when fitting the curve, the amount of weight given to any point is inversely proportional to its distance from the point being estimated (Cleveland et al. 1992). This was done for all geomorphological variables (e.g., slope, aspect, convexity, etc.) and for all spatial averaging buffers (e.g., 0, 30, 50, and 100m spatial averaging radii). The purpose of these *loess* curves is to help in determining potential bin boundaries in a stratification scheme. Once potential bin boundaries are decided on, all fish sites were assigned to new strata (i.e., post-stratification).

Finally, our framework for evaluating design performance is based on examining the trade-off between enhancing the precision of fish biomass estimates and increasing the overall survey effort (i.e., cost) by adding additional sample sizes (Smith et al. 2011, Ault and Smith 2008). To do this, we calculate for each dataset, *n**, or the number of primary units (i.e., survey sites) required to achieve a specified coefficient of variation, CV (here, we use a CV of 20%; Equation 1 below). The resulting *n** for each sampling scheme assumes that the allocation of survey sites among strata places more surveys in larger and more variable strata and fewer surveys in smaller and less variable strata.

Equation 1: $$n^* = \frac{(\sum_h w_h s_h)^2}{V(\bar{D}_{st}) + \frac{1}{N}\sum_h w_h s_h^2}$$

whereby,

$V(\bar{D}_{st}) = (CV[\bar{D}_{st}][\bar{D}_{st}])^2$,

and w_h is the stratum *h* weighting factor,
s_h is the stratum *h* standard deviation among samples,
$V(\bar{D}_{st})$ is the target variance for future surveys of fish biomass
$CV[\bar{D}_{st}]$ is the target coefficient of variation for future surveys of fish biomass
$\bar{D}_{st}$ is the domain-wide estimate of biomass,
N is the total number of primary unit samples, and
s_h^2 is the stratum h variance among samples.

It should be noted that since the geomorphological layers described above contain gaps, then not all fish survey sites have associated geomorphological data, particularly as one varies the spatial averaging buffer from 0 to 100 m. As a result, sample sizes (i.e., the total number of fish survey sites) varied across the different sampling designs. Thus, in order to accurately compare n* for the various datasets, we only include fish survey sites that had geomorphological data for all spatial scales. Furthermore, due to the limited multibeam data for near-shore areas, all fish surveys found in the shallow depth strata (<6 m) were removed. Lastly, any strata that contained fewer than 4 sites, were also removed from the analysis.

Results

Based on inspecting the *loess* curves of all geomorphological metrics, we determined that terrain surface convexity showed the most promise for improving survey design. In other words, the loess curves for terrain surface convexity displayed clear trends for several fish biomass metrics (e.g., Figure 1A), as opposed to a flat line (Figure 1B). Thus, for this preliminary analysis, we focus on terrain surface convexity as our geomorphological variable and report on results for this variable for all spatial scales. To determine bin boundaries, we looked for regions in the *loess* curve that tended to be less than, equal to, or greater than the mean biomass. For example, for planktivores vs. convexity (0m spatial averaging buffer; Figure 1A), biomass is generally below the mean for lower convexity values and above the mean for higher convexity values, corresponding to two convexity bins. The point at which the loess curve intersects the mean biomass line is used to identify bin boundaries (Figure 1A; green lines). For loess curves that revealed no trend (i.e., the curve tended to be equal to the mean; e.g., Figure 1B), no bin bounds were delineated. Based on inspecting these loess curves, we found relatively broad agreement in bin boundaries for the same fish indicator across different spatial scales (Table 1). For example, primary consumers, parrotfishes, and 0 – 20 cm fishes had similar bin boundaries across all spatial scales. On the other hand, the loess curves for secondary consumers, piscivores, and 50+ cm fishes showed no trends at any spatial scale. Overall, we decided on 0.3 and 0.5 as our convexity bin boundaries, with 0 to 0.3, 0.3 to 0.5, and 0.5 to 1.0 corresponding to low, moderate, and high convexity strata. For all other loess curves see Appendix A.

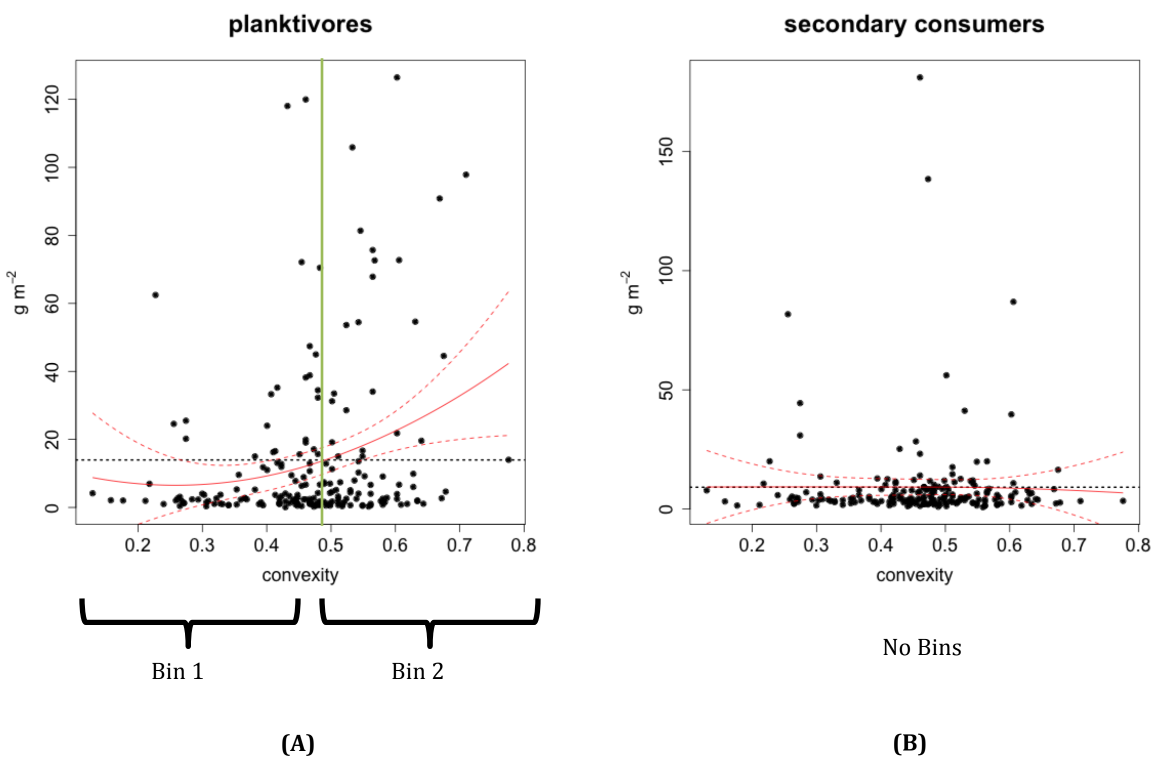

Figure 1. Fish biomass for planktivores (A) and secondary consumers (B) vs. terrain surface convexity for sites around Tutuila, American Samoa. Displayed on each graph are the site-level survey data (points), global mean (black dotted line), loess curve (red solid line), and 95% confidence intervals (red dotted line). The biomass of planktivores (A) appears to trend with convexity, justifying the delineation of bins, or strata, with regards to convexity. On the other hand, the biomass of secondary consumers appears to have no relationship with convexity.

Based on these bin boundaries, each fish survey site was assigned to a strata based on their depth and convexity characteristics (i.e., post-stratification). The full complement of possible stratification schemes were then compared by calculating for each the number of samples (*n**) required in a future survey to achieve a CV of 20% (Table 2). For most fish indicators, using a combination of depth and convexity turned out to be the most efficient sampling scheme (i.e., had the lowest n*; Table 2).

Table 1: Bin boundaries of terrain surface convexity for all fish biomass indicators and all spatial scales based on inspection of loess curves

Scale[1]	Fish Indicator	Bin Bounds
0	Total Fish	NA
	Primary	0.3, 0.5
	Secondary	NA
	Planktivore	0.5
	Piscivore	NA
	Parrotfish	0.3
	0 - 20 cm	NA
	20 - 50 cm	NA
	50+ cm	NA
30	Total Fish	0.45
	Primary	0.25, 0.5
	Secondary	NA
	Planktivore	0.45
	Piscivore	NA
	Parrotfish	0.3
	0 - 20 cm	NA
	20 - 50 cm	0.45
	50+ cm	NA
50	Total Fish	0.45
	Primary	0.3, 0.5
	Secondary	NA
	Planktivore	0.45
	Piscivore	NA
	Parrotfish	0.3, 0.5
	0 - 20 cm	NA
	20 - 50 cm	0.45
	50+ cm	NA
100	Total Fish	NA
	Primary	0.3, 0.5
	Secondary	NA
	Planktivore	0.45
	Piscivore	NA
	Parrotfish	0.35
	0 - 20 cm	NA
	20 - 50 cm	0.45
	50+ cm	NA
Overall Bin Bounds		0.3, 0.5

[1]Length of spatial averaging buffer (m)

Table 2. Post-stratification analysis results for eight fish biomass indicators based on CRED fish surveys conducted around Tutuila, American Samoa. For each fish indicator, the most efficient survey design is in bold.

Fish Indicator	Stratification variables	Survey-wide Mean Biomass	Standard Error	n* (20%)
Total Fish	Depth	52.35	5.32	34
	Depth, Convexity 0m	52.17	5.80	18
	Depth, Convexity 30m	52.73	5.50	18
	Depth, Convexity 50m	53.19	5.44	26
	Depth, Convexity 100m	54.23	5.36	19
Primary	Depth	17.04	0.84	11
	Depth, Convexity 0m	16.81	0.82	9
	Depth, Convexity 30m	17.19	0.88	10
	Depth, Convexity 50m	16.82	0.84	12
	Depth, Convexity 100m	17.11	0.87	13
Secondary	Depth	9.14	1.35	69
	Depth, Convexity 0m	8.97	1.42	75
	Depth, Convexity 30m	9.11	1.40	59
	Depth, Convexity 50m	9.44	1.51	71
	Depth, Convexity 100m	9.58	1.53	75
Planktivore	Depth	14.71	1.82	50
	Depth, Convexity 0m	14.48	1.80	36
	Depth, Convexity 30m	14.79	1.82	37
	Depth, Convexity 50m	15.19	1.89	49
	Depth, Convexity 100m	15.96	2.03	49
Piscivore	Depth	11.46	4.01	110
	Depth, Convexity 0m	11.90	4.53	19
	Depth, Convexity 30m	11.64	4.19	21
	Depth, Convexity 50m	11.75	4.13	51
	Depth, Convexity 100m	11.58	3.87	31
Parrotfish	**Depth**	7.50	0.63	30
	Depth, Convexity 0m	7.28	0.60	31
	Depth, Convexity 30m	7.61	0.68	35
	Depth, Convexity 50m	7.17	0.61	37
	Depth, Convexity 100m	7.43	0.65	38
0-20cm	Depth	17.95	0.95	12
	Depth, Convexity 0m	17.78	0.92	19
	Depth, Convexity 30m	17.92	0.93	20
	Depth, Convexity 50m	18.25	1.02	12
	Depth, Convexity 100m	18.15	0.98	11
20-50cm	Depth	24.23	2.24	32
	Depth, Convexity 0m	23.71	2.20	26
	Depth, Convexity 30m	24.40	2.25	28
	Depth, Convexity 50m	24.49	2.30	29
	Depth, Convexity 100m	25.37	2.45	30
50cm+	Depth	10.17	4.20	135
	Depth, Convexity 0m	10.68	4.74	48
	Depth, Convexity 30m	10.41	4.39	44
	Depth, Convexity 50m	10.46	4.35	95
	Depth, Convexity 100m	10.71	4.12	90

Discussion

Overall, we found that adding convexity as a second stratum variable enhanced our sampling design efficiency when compared to just using depth alone. This was true for all fish biomass indicators except parrotfishes. For parrotfishes, the original sampling design using only depth as a stratum variable performed better. On the other hand, piscivores benefited the most from adding convexity as a strata. Using the original depth-stratified sampling design required 110 samples to achieve our target CV for piscivores. This was reduced to just 19 samples when using depth and convexity to stratify samples. Biomass of fish greater than 50cm and total fish biomass also appeared to benefit significantly from the addition of convexity as a stratum variable.

One should exercise caution, however, in making generalizations of patterns across the different fish indicator groups. Previous attempts to compare across studies found that the relationships between remotely-sensed geomorphology and fish assemblages were widely varied, with biogeography and reef types among some of the factors (Mellin 2009). Thus, while it is true that different species and different families of fish can be expected to show individualized responses (Pittman and Brown 2011), it is unclear at this time why the estimation of piscivore biomass was facilitated so greatly with the inclusion of convexity information.

In the future, we intend to explore more systematic possibilities for visualizing fish-geomorphology trends and determining bin boundaries (Appendix A). Curiously, while piscivores achieved a lower n^* whenever convexity was included as part of a depth-convexity stratified sampling design, piscivore data did not reveal any obvious trends with convexity alone. The strategy of using *loess* curves to explore overall trends in the data was mainly used as an exploratory tool. There may be more sophisticated techniques for binning data with the goal of lowering variance in each bin. In fact, there are potential algorithms for doing this (e.g., R package *SamplingStrata*) that should be included in future analyses.

Indeed, there are some notable limitations to the preliminary data analysis described here. First, due to the exclusion of bathymetric data derived from IKONOS satellite imagery, many fish survey sites were excluded from the analysis due to a lack of benthic geomorphological data. Since the bathymetric gaps were mainly found in shallow areas, we removed all shallow fish survey sites from our analysis. Thus, not all depth strata were equally represented in our analysis. Furthermore, the analysis was limited to Tutuila, American Samoa. This location was chosen as our pilot site because it was believed to have one of the more complete bathymetry datasets out of the islands surveyed by CRED. It was subsequently decided to exclude the shallow bathymetry derived from IKONOS imagery. Future analyses should try to incorporate shallow habitats using a combination of multibeam and LiDAR bathymetry data and expand this analysis to other islands and regions.

Lastly, it appears that the spatial averaging buffers did not produce any clear trends. No matter what spatial scale was used (0 to 100 m), including convexity in the sampling design reduced n^* by a similar amount as compared to depth alone. Across all fish indicator groups, the best sampling design used depth and convexity at 0 m, highlighting the importance of fine-scale benthic data. While they did not always result in the best sampling designs, medium and large-scale convexity (e.g., 30, 50, and 100 m buffers) were still able to improve sampling design and reduce n^*. Further analysis must be done in order to understand the general effect of averaging cells across different spatial scales.

In summary, this preliminary study demonstrates that terrain surface convexity can be used to improve the sampling designs of reef fish assemblages around Tutuila, American Samoa. The utility of terrain surface convexity for improving survey design, however, will not be known until this same analysis is applied to other geographic areas. Furthermore, with this analytical framework now in place, we intend to examine other variables besides terrain surface convexity to allow for comparisons to be made between the different geomorphological metrics and broader conclusions to be made about the best way forward for improving reef fish survey designs.

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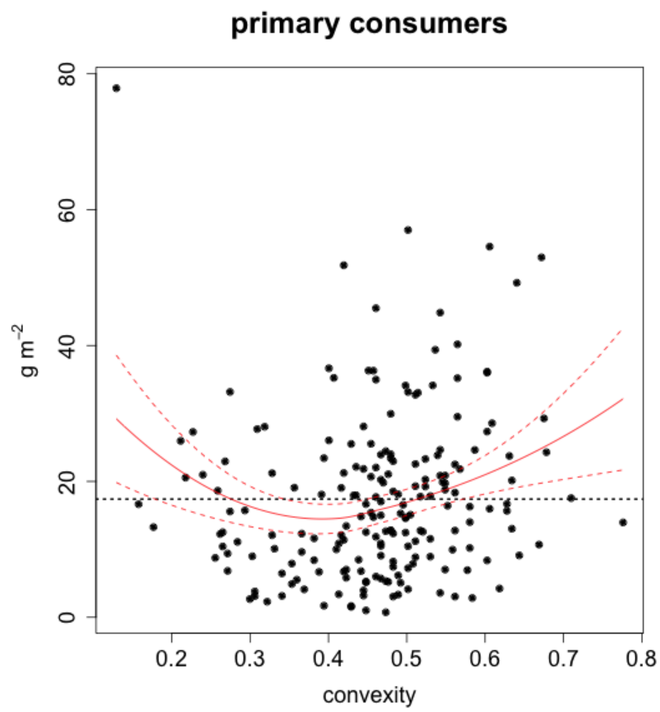
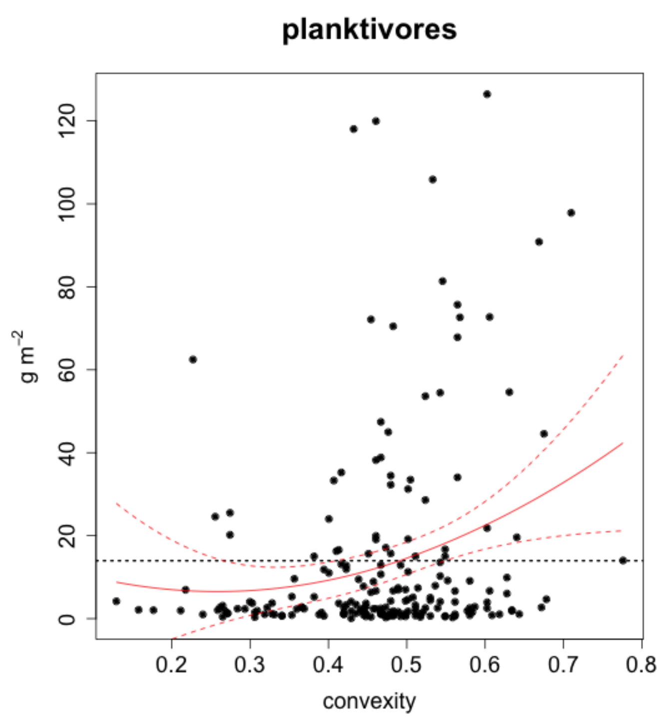
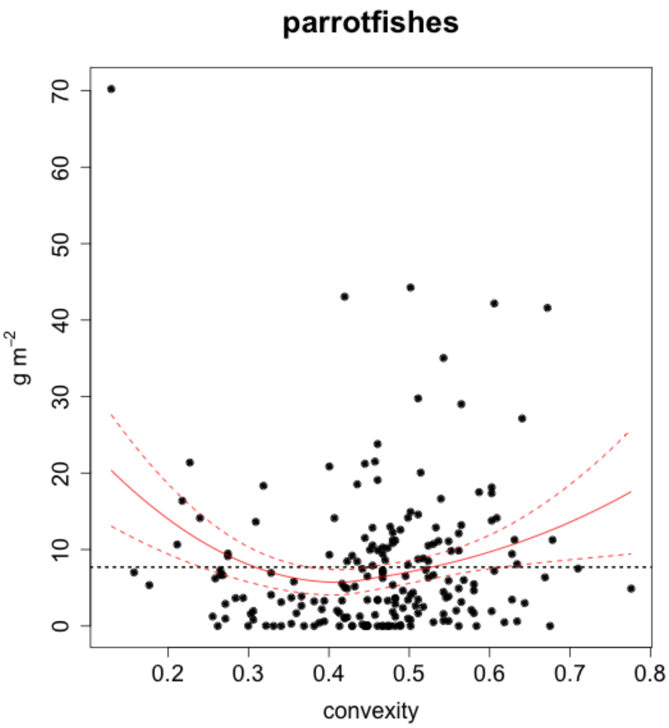
Appendix A.1: Surface terrain convexity with 0 m spatial buffer vs. biomass for different fish indicator groups for Tutuila, American Samoa:

Only indicator groups that show a trend with convexity are shown here. Displayed on each graph are the survey data (points), global mean (black dotted line), loess curve (red solid line), and 95% confidence intervals (red dotted line).

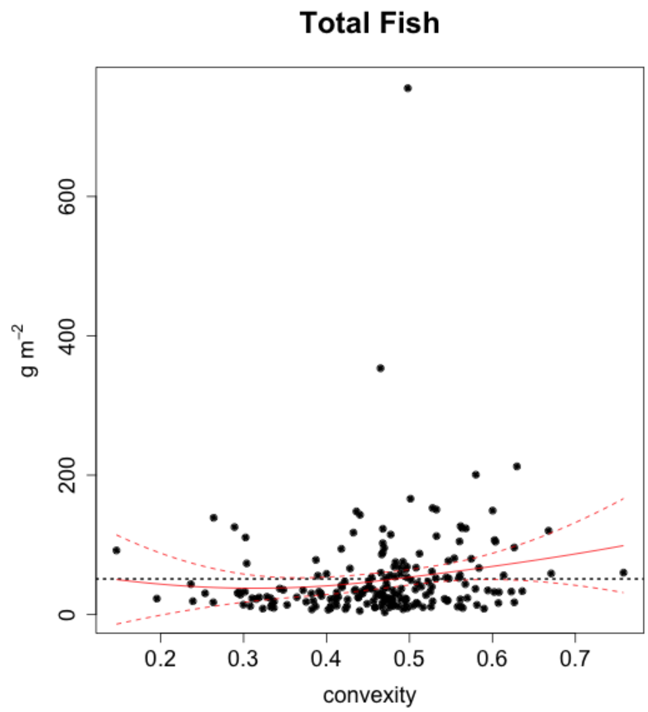


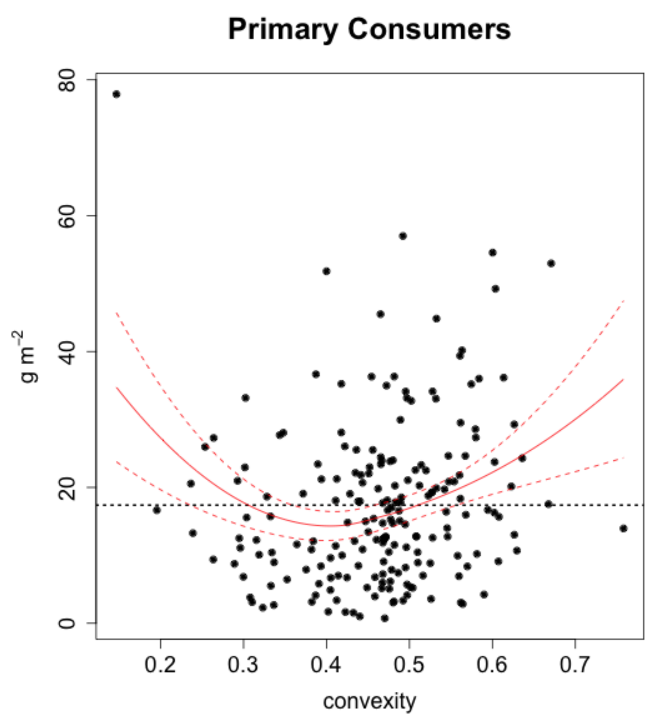


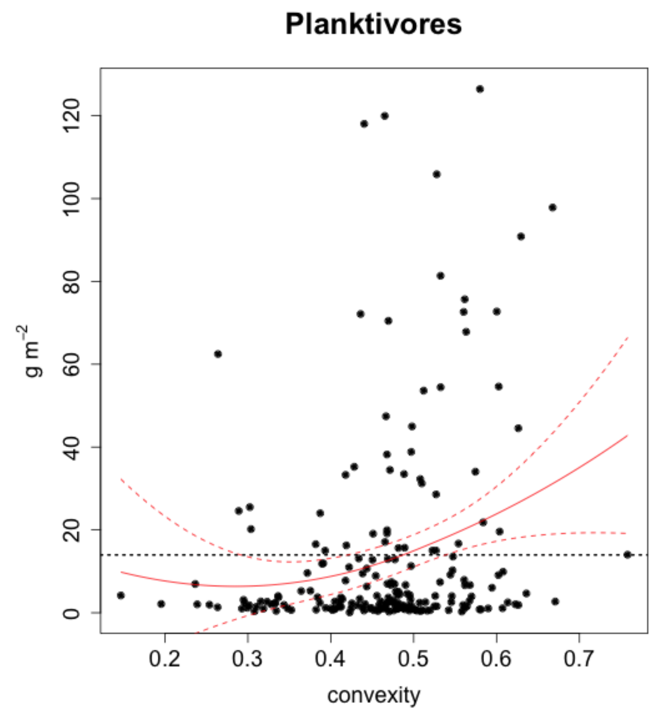

parrotfishes
g m^{-2}
0
10
20
30
40
50
60
70
0.2
0.3
0.4
0.5
0.6
0.7
0.8
convexity

Appendix A.2: Surface terrain convexity with 30 m spatial buffer vs. biomass for different fish indicator groups for Tutuila, American Samoa.

Only indicator groups that show a trend with convexity are shown here. Displayed on each graph are the survey data (points), global mean (black dotted line), loess curve (red solid line), and 95% confidence intervals (red dotted line).






Planktivores
g m^-2
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100
120
0.2
0.3
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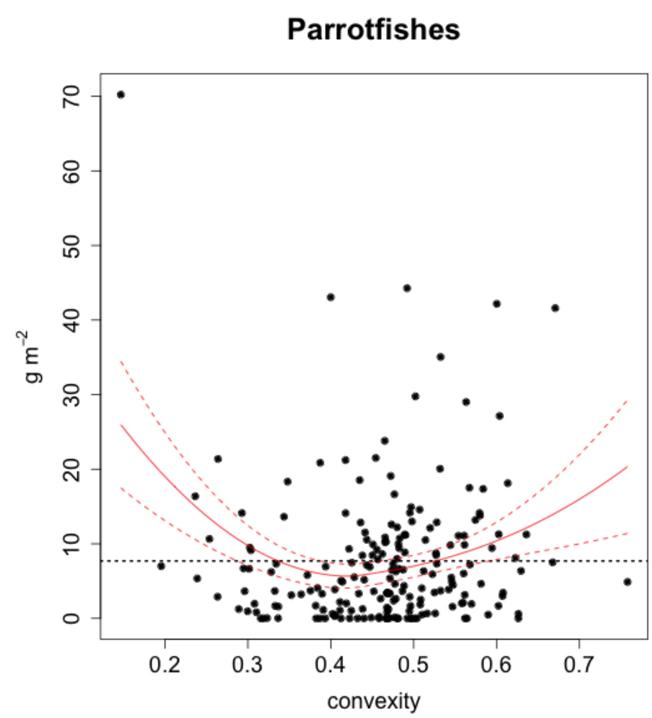
0.7
convexity


Parrotfishes
g m^-2
0
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20
30
40
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60
70
0.2
0.3
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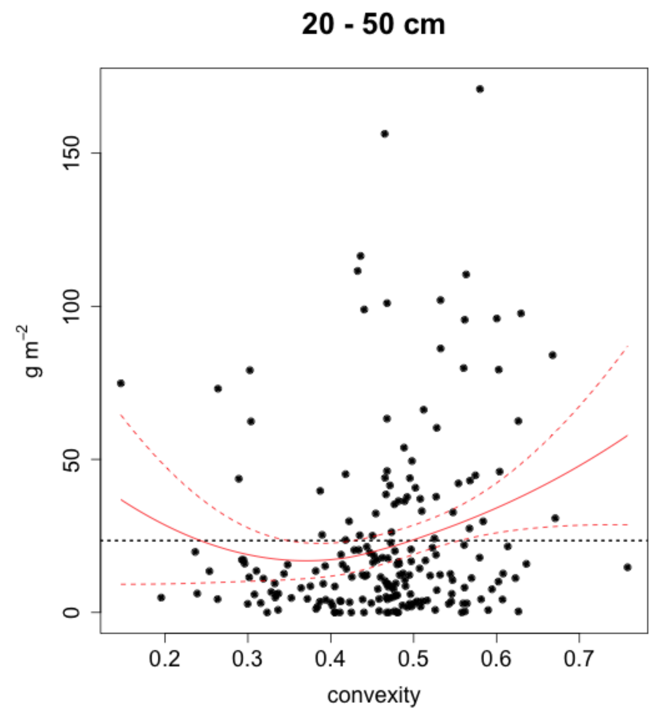
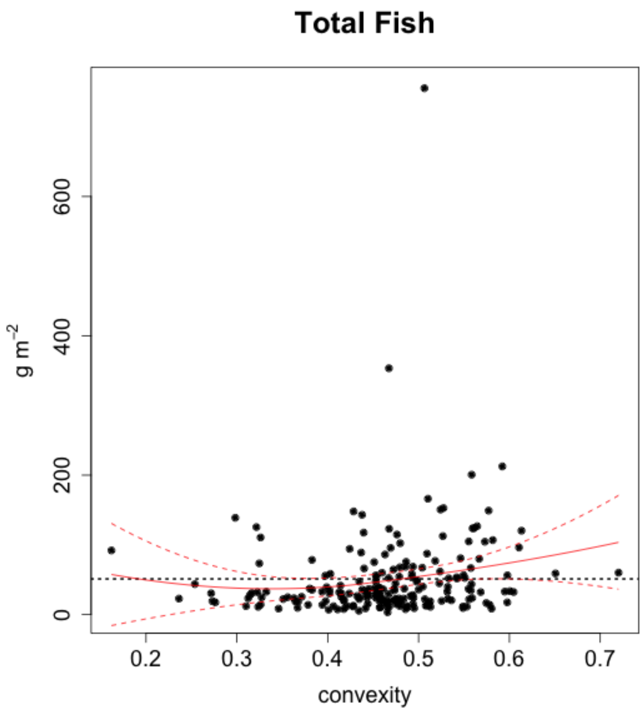
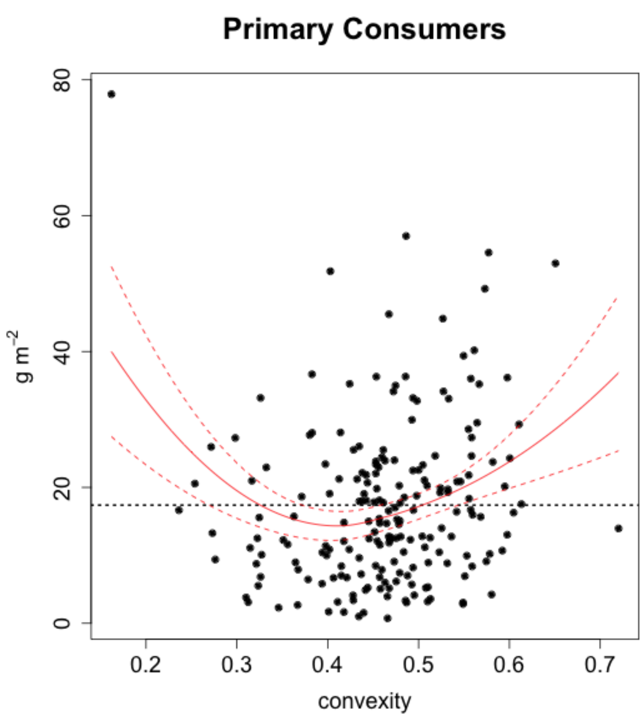
0.6
0.7
convexity

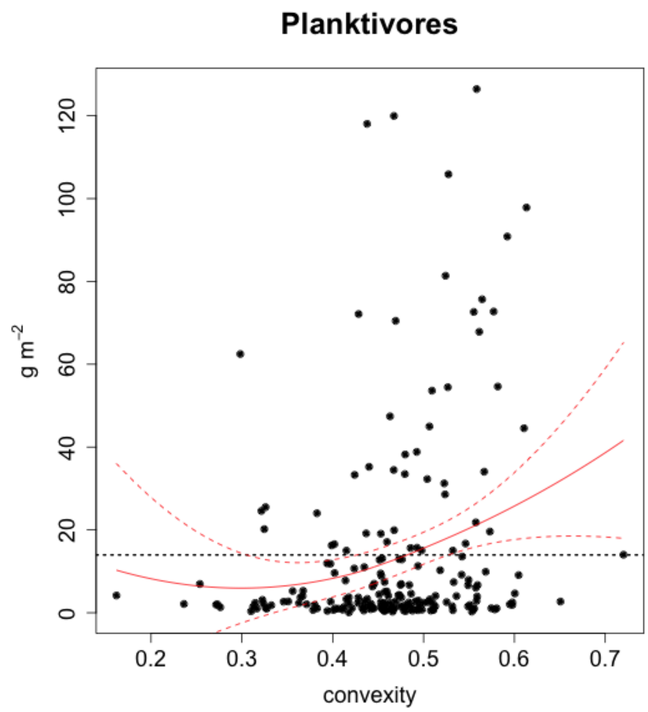

20 - 50 cm
g m^-2
0
50
100
150
0.2
0.3
0.4
0.5
0.6
0.7
convexity

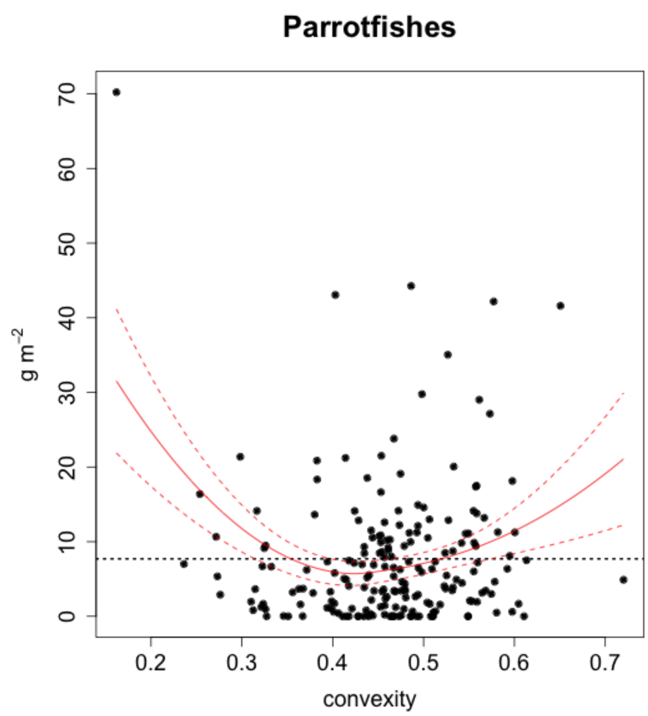
Appendix A.3: Surface terrain convexity with 50 m spatial buffer vs. biomass for different fish indicator groups for Tutuila, American Samoa:

Only indicator groups that show a trend with convexity are shown here. Displayed on each graph are the survey data (points), global mean (black dotted line), loess curve (red solid line), and 95% confidence intervals (red dotted line).

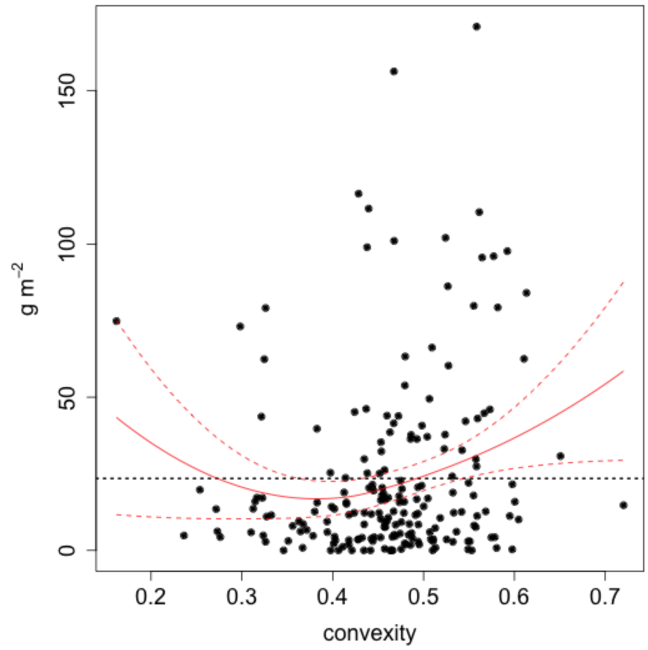





Planktivores
g m^{-2}
0
20
40
60
80
100
120
0.2
0.3
0.4
0.5
0.6
0.7
convexity

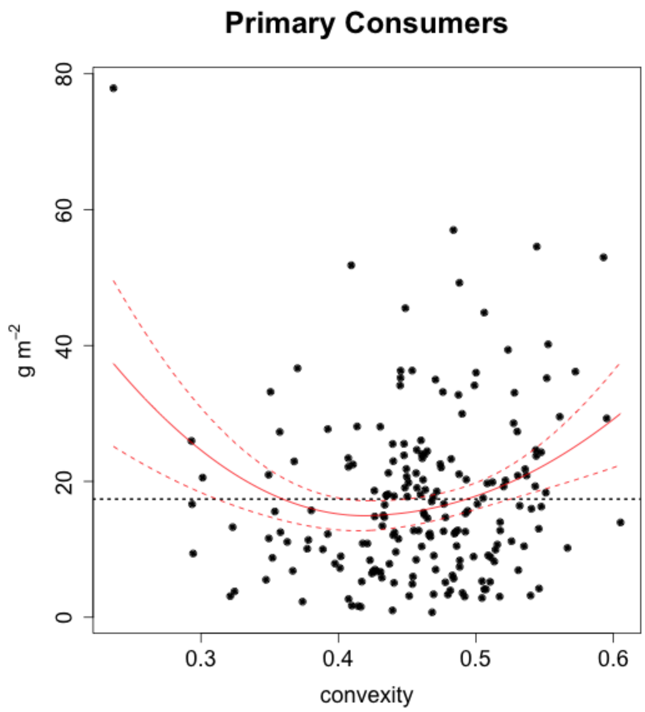

Parrotfishes
g m^{-2}
0
10
20
30
40
50
60
70
0.2
0.3
0.4
0.5
0.6
0.7
convexity

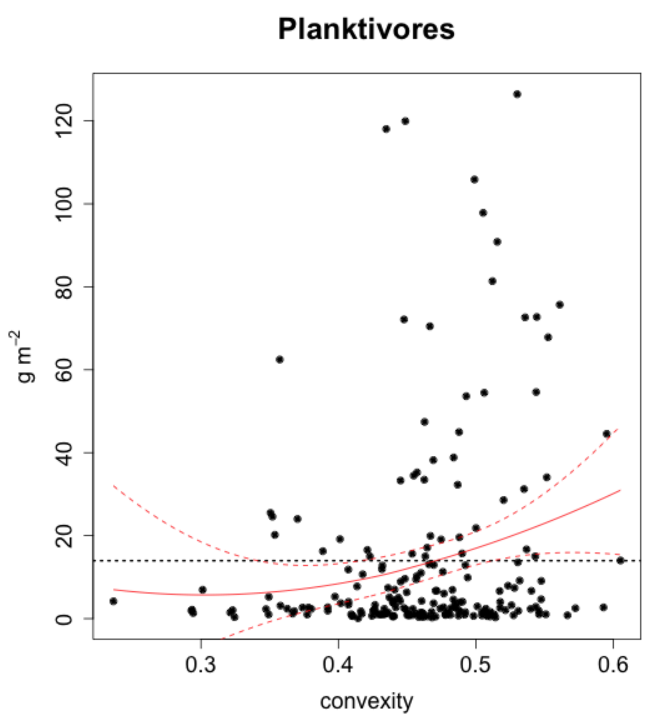
20 - 50 cm

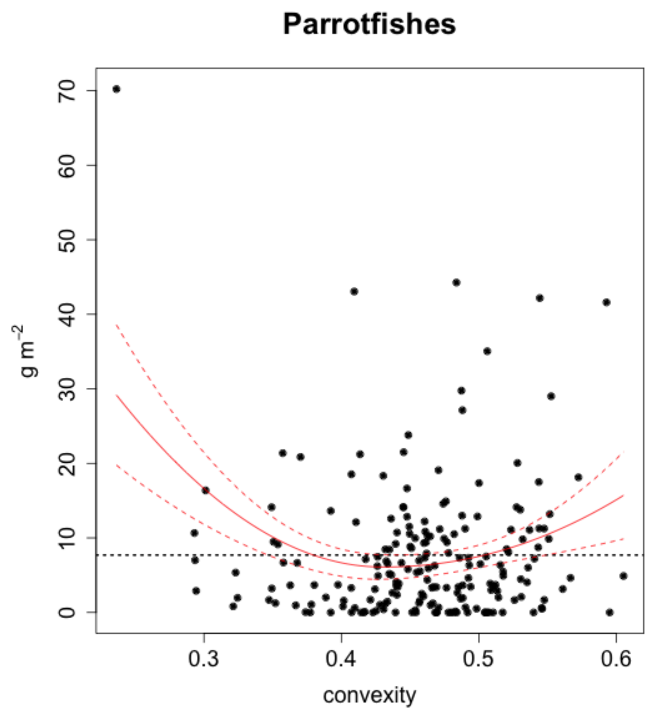


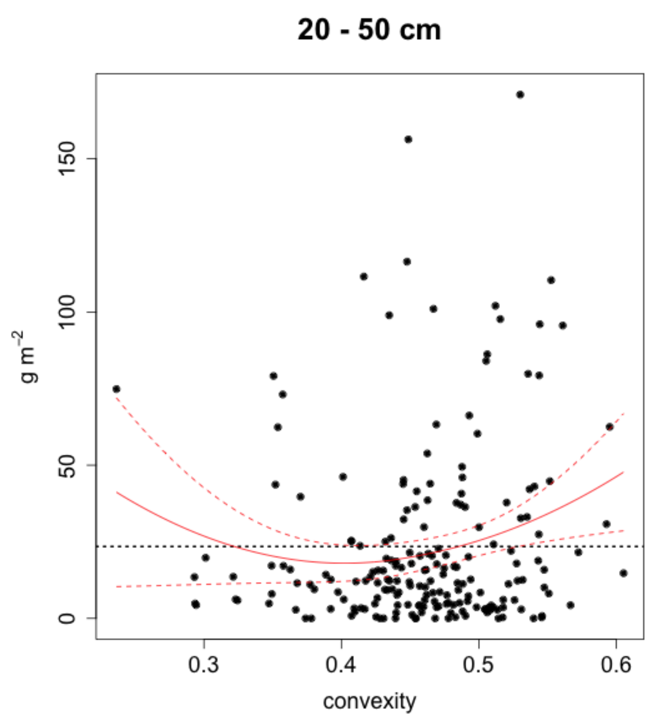
Appendix A.4: Surface terrain convexity with 100 m spatial buffer vs. biomass for different fish indicator groups for Tutuila, American Samoa:

Only indicator groups that show a trend with convexity are shown here. Displayed on each graph are the survey data (points), global mean (black dotted line), loess curve (red solid line), and 95% confidence intervals (red dotted line).






Parrotfishes
g m^{-2}
0
10
20
30
40
50
60
70
0.3
0.4
0.5
0.6
convexity


20 - 50 cm
g m^{-2}
0
50
100
150
0.3
0.4
0.5
0.6
convexity