A Survey Design Performance Analysis Examining Linkages between Reef Fish Assemblages and Benthic Morphologies in the Main Hawaiian Islands

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Introduction

Coral reefs are structurally complex and heterogeneous marine ecosystems whose physical structure is known to influence ecological processes such as predation, competition, and recruitment (Hixon and Beets, 1993). Many species of reef fish depend on 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 associations between fish assemblages and geomorphological benthic 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 biogeographical differences and the different spatial scales being considered (Mellin et al., 2009).

Understanding the relationships that link reef fish assemblages with their underlying habitats is important to conservation practitioners and managers. For example, 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 (i.e., marine spatial planning, Pittman and Brown, 2011). From a fisheries management perspective, developing an improved understanding of linkages between fishes and their habitat is important for identifying legislatively defined ‘essential fish habitat’ and for reducing 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., survey domain) is partitioned into discreet strata, and the amount of survey effort (e.g., the number of surveys) allocated to each stratum is based on its area and variance.

The latter is most related to the Coral Reef Ecosystem Program (CREP) and its implementation of the Pacific Reef Assessment and Monitoring Program (Pacific-RAMP). CREP uses a stratified random survey design, but currently, only depth and reef zone are typically used as environmental correlates. Here, we derive several geomorphologic characteristics from bathymetric LiDAR data and investigate their relationship to different fish assemblage summary metrics collected from underwater visual census surveys. Specifically, we explore the possibility of adding geomorphological strata to the CREP reef fish survey design. We do this by comparing survey design efficiency of depth-only stratification vs. depth and geomorphology stratification. Overall, our goal is to use this enhanced understanding of habitat-biota relationships to improve future reef fish survey designs.

Materials and Methods

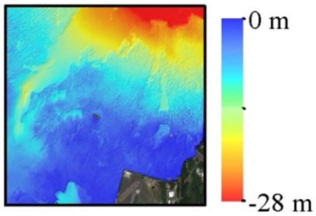
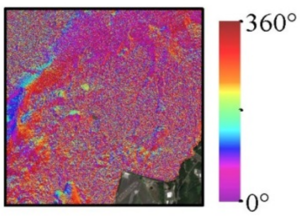
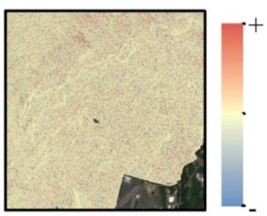
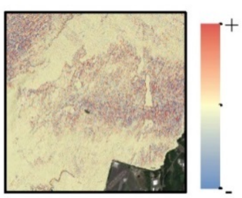
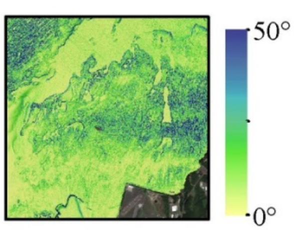
Geomorphologic Benthic Characteristics

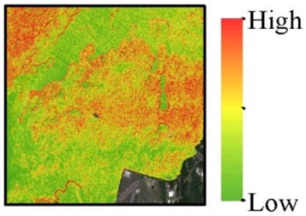
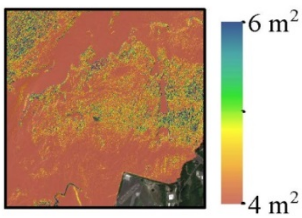
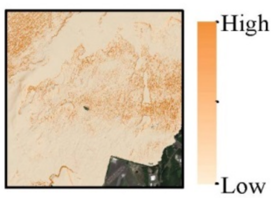
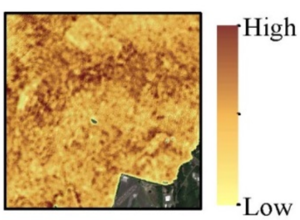
Two bathymetric data sets were initially considered for deriving the geomorphologic benthic habitat characteristics. A synthesis of bathymetric data gridded at 5-m spatial resolution was provided by the University of Hawaii, Hawaii Mapping Research Group (HMRG). Geometric distortions were observed across these bathymetric data. These distortions were likely generated due to spatial interpolation of multiple sources of data points at various spatial resolution producing local extrema at data points (Appendix A). The distortions were exacerbated on derivation of the geomorphologic features. Therefore, the 5-m bathymetric synthesis was excluded from our analysis.

The aerial topographic and bathymetric LiDAR collected in 2013 by Joint Airborne LiDAR Bathymetry Technical Center of Expertise with funding provided by the US Army Corps of Engineers (USACE) National Coastal Mapping Program (NCMP) (USACE NCMP, 2016) around most of the main Hawaiian Islands was used to derive geomorphologic benthic characteristics. The data were adjusted to the local mean sea level (LMSL). The bathymetric LiDAR points were gridded at 2-m pixel resolution. The cell values in this data set represent the minimum depth measurement found within each cell, or if there were no values in the cell, a value have been interpolated from surrounding cells with data values using Inverse Distance Weighting method.

We derived a series of benthic geomorphology variables for the nearshore environment of Kauai, Oahu, Molokai, Lanai, Maui and Hawaii Islands where the 2013 bathymetric LiDAR is available. The open source GIS software, System for Automated Geoscientific Analysis (SAGA) version 2.1.4 (Conrad et al., 2015) was used for the processing. A total of nine geomorphology variables were derived for this study: depth, aspect, rugosity, plan curvature, profile curvature, slope, slope of slope, real surface area, and terrain surface convexity. Each variable and tools to derive them is described in Table 1. Watkins (2015) describes further details on calculating each of these benthic geomorphology variables.

Table 1. List of benthic geomorphology variables derived from LiDAR. The base imagery shows Kaneohe Bay, Oahu

Geomorphology Variables	**Description**
Depth (m) 	Depth is distance from the sea surface to the bottom of the ocean. The bathymetric LiDAR data collected around the main Hawaiian Islands in 2013 were used in the analysis. The data were adjusted to local mean sea level, and gridded at 2-m pixel resolution. The cell values in the data represent the minimum depth measurement found in each cell.
Aspect (°) 	Aspect shows the compass direction that the surface faces at a cell. It can be thought of as slope direction. It is derived with the Slope, Aspect, Curvature tool using the nine parameter second-order polynomial method (Zevenbergen and Thorne, 1987). Values range from 0 to 360 degrees.
Plan Curvature 	Plan curvature is perpendicular to the direction of the maximum slope. A positive value indicates the surface is horizontally convex at that cell, while a negative value indicates horizontally concave at that cell. A value of zero indicates the surface is linear. It is derived with the Slope, Aspect, Curvature tool using the nine parameter second-order polynomial method (Zevenbergen and Thorne, 1987).
Profile Curvature 	Profile curvature is parallel to the direction of the maximum slope. A negative value indicates that the surface is upwardly convex; a positive value, concave. Zero indicates a linear surface. It is derived with the Slope, Aspect, Curvature tool using the nine parameter second-order polynomial method (Zevenbergen and Thorne, 1987).
Slope (°) 	Slope is the maximum change in depth over distance between the cell and its neighboring cells. It is derived with the Slope, Aspect, Curvature tool using the nine parameter second-order polynomial method (Zevenbergen and Thorne, 1987). Values range from 0 to 90 degrees.

Geomorphology Variables	Description
Slope of Slope 	Slope of slope is maximum rate of maximum slope change between the cell and its neighboring cells (Pittman et al., 2009). It is a second derivative of bathymetry. Unit is degrees of degrees. It is derived with the Slope, Aspect, Curvature tool using the nine parameter second-order polynomial method (Zevenbergen and Thorne, 1987).
Surface Area (m^2) 	Real surface area (Grohmann et al., 2009) is derived using Real Surface Area tool. This is a measure of surface roughness. Rougher surfaces have greater surface areas.
Rugosity 	Rugosity (or surface area ratio) is derived by dividing real surface area by the geometric surface area (or planimetric area). This is a unitless measure of surface roughness. The minimum value is 1 and indicates flat surface.
Terrain Surface Convexity 	Terrain surface convexity is measured as the percentage of convex-upward cells within a constant radius of ten cells (Iwahashi and Pike, 2007). It is derived using Terrain Surface Convexity tool.

Sources: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community. The scale bar for each image shows the range of values within the extent of the map.

For each of the benthic geomorphology variables described above, site-specific values were extracted for each fish survey location in the main Hawaiian Islands using ESRI's ArcToolbox. In addition, it has long been recognized that different metrics of fish communities respond to different scales of their environment (Mellin et al., 2009). Since we do not know the specific spatial scale that would be most important for our study, we employ a multi-scale approach and calculate the average and standard deviation of all geomorphology values within radii of 15, 25, and 50 m (i.e., diameters of 30, 50, and 100 m) of each input cell location and extract this information for each GPS location of fish survey. This was conducted to characterize the geomorphology of each survey location at four spatial scales: one that is based on the site-specific geomorphology value for each fish survey (0 m), and three that are based on averaging all cells within 15, 25, and 50 m of the survey site. Thus, this framework allowed us to investigate linkages between fish biomass and multiple scales of benthic structure. A list of all geomorphological variables tested here can be found in Table 2.

Table 2. List of all combinations of geomorphological metrics, spatial scales, and summary metrics tested as potential stratification variables.

Geomorphological Variable	Spatial Scale	Summary metric
Aspect	0	Point-value
	30	Mean
		Standard Deviation
	50	Mean
		Standard Deviation
	100	Mean
		Standard Deviation
Plan Curvature	0	Point-value
	30	Mean
		Standard Deviation
	50	Mean
		Standard Deviation
	100	Mean
		Standard Deviation
Profile Curvature	0	Point-value
	30	Mean
		Standard Deviation
	50	Mean
		Standard Deviation
	100	Mean
		Standard Deviation
Rugosity	0	Point-value
	30	Mean
		Standard Deviation
	50	Mean
		Standard Deviation
	100	Mean
		Standard Deviation
Slope	0	Point-value
	30	Mean
		Standard Deviation
	50	Mean
		Standard Deviation
	100	Mean
		Standard Deviation
Slope of Slope	0	Point-value
	30	Mean
		Standard Deviation
	50	Mean
		Standard Deviation
	100	Mean
		Standard Deviation

Geomorphological Variable	Spatial Scale	Summary metric
Surface Area	0	Point-value
	30	Mean
		Standard Deviation
	50	Mean
		Standard Deviation
	100	Mean
		Standard Deviation
Terrain Surface Convexity	0	Point-value
	30	Mean
		Standard Deviation
	50	Mean
		Standard Deviation
	100	Mean
		Standard Deviation

Fish Variables

Fish data were collected around islands in main Hawaiian Islands in the years 2010, 2012, 2013, 2015, and 2016 using identical methods as part of Pacific RAMP. Prior to each field season, fish survey sites were 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 3 depth strata (shallow or 0–6 m; mid-depth or > 6–18 m; and deep or > 18–30 m). At each survey site, paired divers collected replicate data on fish sizes and counts using a stationary point count (SPC) method. The surveys consisted of: (i) a 5-min enumeration period when divers recorded all fish species that passed through a visually estimated cylinder of 7.5-m radius and (ii) a tallying period when divers recorded 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 were then converted to fish biomass (g m^{-2}). Fish biomass were 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 9 fish biomass indicators, including 4 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 priority indicators by the NOAA National Coral Reef Monitoring Plan (NOAA Coral Program, 2014; Heenan et al., 2015; McCoy et al., 2017; McCoy et al., 2016).

Design Performance

A total of 803 fish surveys with benthic geomorphology data were used in this analysis (195 deep strata, 387 mid-depth strata, and 221 shallow strata surveys). The first step was to look for trends between each of the 9 fish biomass indicators and each of the 8 geomorphological metrics (each of which was listed in Table 1. For each fish-geomorphological pairing, we calculated the mean biomass of all fish surveys in the data set, and used local polynomial regression fitting (loess, $\alpha = 1.5$) 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 moving averages and standard deviations (e.g., 0-, 30-, 50-, and 100-m spatial scale). The purpose of these loess curves is to help in determining potential strata boundaries in a stratification scheme. Once potential strata boundaries were decided, all fish sites were assigned to new strata that were now based on geomorphology and depth (i.e., post-stratification), thus allowing us to compare each new stratification design to the original design based only on depth.

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 calculated for each data set, *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 more variable strata and fewer surveys in 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, or the proportion of the stratum area relative to the total survey area

s_h is the stratum h standard deviation in fish biomass,

$V(\bar{D}_{st})$ 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 in fish biomass.

Due to gaps in the geomorphological layers described above, the number of fish survey sites with associated geomorphological data varies across the different spatial scales of averaging buffers. Thus, in order to accurately compare *n** for the various data sets, we only include fish survey sites that had geomorphological data for all spatial scales. Luckily, the Pacific RAMP reef fish dataset is relatively large with 1185 sites surveys conducted between 2010 and 2016; even after filtering out fish surveys with incomplete geomorphological metrics, a total of 804 fish surveys were retained for our analysis.

Finally, a separate synthesis bathymetric data set available from HMRG (from here on, "synthesis maps") was used to derive the same geomorphology metrics at a coarser spatial scale. These synthesis maps are integrated into CREP's current survey design, which stratifies effort based only on depth. The advantage of these maps is they have greater spatial coverage of our target domain (hard-bottom habitats between 0 and 30 m). The disadvantage, however, is that they are much coarser (50-m × 50-m resolution). The purpose of this final step was to demonstrate whether this approach of stratifying based on depth and geomorphology could be put into practice, even for areas of the Pacific where we do not have high-resolution LiDAR data.

Results

Based on visually inspecting the loess curves of all geomorphological metrics, we determined that mean rugosity, mean slope, mean slope of slope, and standard deviation of profile curvature showed the most promise for improving fish survey design. For each of their loess curves, we see that low measures of the geomorphology metric are significantly less than (based on 95% confidence intervals) the global mean for fish biomass, while high measures of the geomorphology metric are significantly greater than the global mean. In other words, the loess curves for each of these geomorphologies displayed clear trends with total reef fish biomass (e.g., Figure 1A; Appendix B), as well as with several other indicator groups of fish biomass as opposed to a flat line (Figure 1B).

Conversely, the following metrics were not considered further, either because their loess curve showed no trend with fish biomass (i.e., displayed a flat line; Appendix C), or if the metric's distribution was overly skewed (e.g., mean surface area; Appendix C): mean aspect, mean convexity, mean planar curvature, mean profile curvature, and mean surface area, as well as all standard deviation metrics except that for profile curvature.

The remaining analyses focused on these four candidate geomorphology metrics: mean rugosity, mean slope, mean slope of slope, and standard deviation of profile curvature. Furthermore, in terms of spatial scale, we found increasing correlations between fish biomass at larger scales (50 and 100 m) as opposed to smaller scales. The difference in correlation between spatial scales was relatively small (e.g., for slope of slope, correlation with total reef fish biomass increased from 0.15 at 0 m to 0.28 at 100 m), however, this pattern of increasing correlation for larger scales was consistent for all four candidate geomorphology metrics. One possible explanation is that large, roving predators, which tend to add stochastic noise to reef fish data, are correlated more with these larger scale geomorphologies, thus driving this pattern of increased correlation at larger scales. Others have suggested that the home range of a fish species is an important factor in determining to what environmental spatial scale the species will respond, but it is difficult to generalize across species due to the limited number of species with information on home-ranging behavior (Pittman and Brown, 2011). Since the final step in our analysis was to compare LiDAR-derived metrics with metrics derived from the coarser 50-m × 50-m synthesis maps, we focused our analysis of LiDAR metrics at the 50-m spatial scale.

To determine the strata boundaries for each geomorphological metric, 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 slope of slope, total fish biomass is generally below the mean for lower slope of slope values and above the mean for higher slope of slope values, corresponding to two strata.

The point at which the loess curve intersects the mean biomass line was used to identify strata boundaries (Figure 1A; green line).

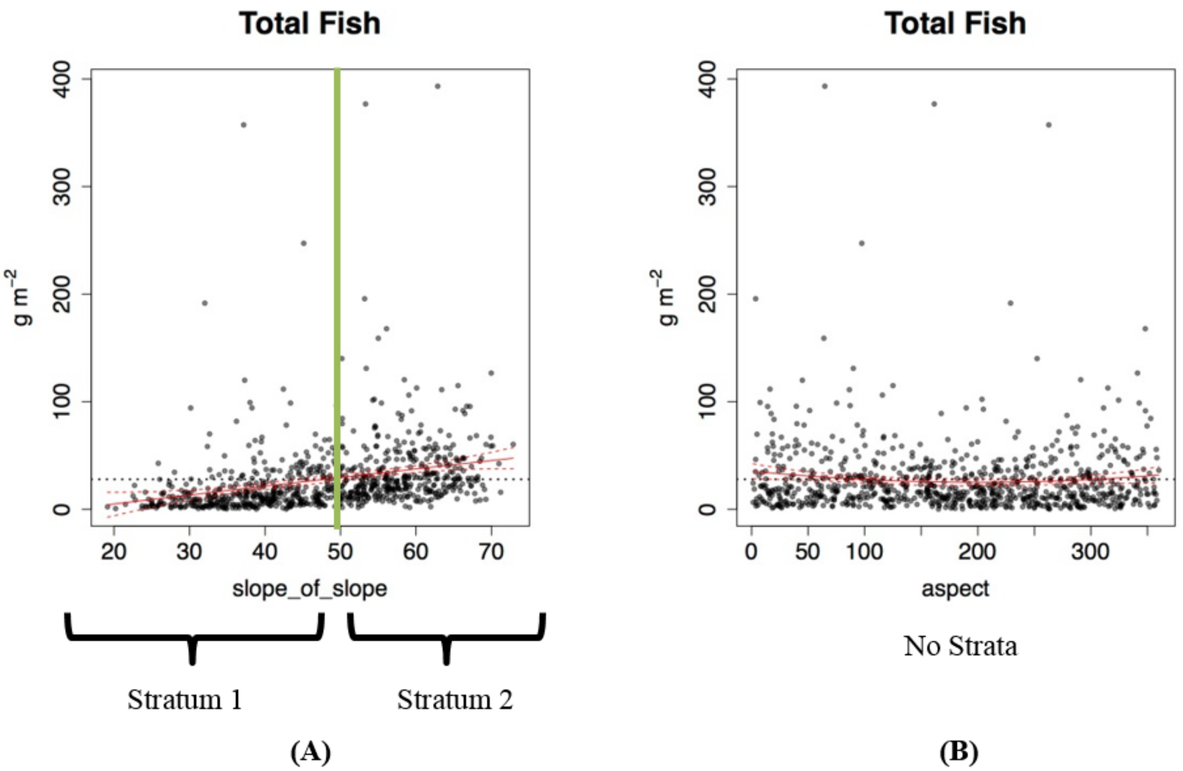


Figure 1. Fish biomass for total reef fish biomass vs. slope of slope (A) and aspect (B) for sites in the main Hawaiian Islands.

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). Total reef fish biomass appears to trend with slope of slope, justifying the delineation of strata with regards to slope of slope. The green line represents the boundary between low and high slope of slope. On the other hand, total reef fish biomass appears to have no relationship with aspect.

For a given geomorphology metric, we found relatively broad agreement in strata boundaries across different spatial scales as well as across fish biomass indicators. For example, for slope, the strata boundary between low slope and high slope was similar across all spatial scales (Figure 2) as well as for various fish biomass indicators (Figure 3). Strata boundaries for mean rugosity, mean slope, mean slope of slope, and standard deviation of profile curvature can be found in Table 3.

Table 3. Strata boundaries for various geomorphology metrics based on inspection of loess curves.

Geomorphology	Strata Boundary
Mean Rugosity	1.025
Mean Slope	8
Mean Slope of Slope	50
Profile Curvature Standard Deviation	0.1

Loess curves for the geomorphology metrics that displayed a trend with total reef fish biomass based on visual inspection of loess curves as described above (i.e., mean rugosity, mean slope, mean slope of slope, standard deviation of profile curvature) can be found in Appendix B. A total of 640 loess curves were created for this study, each displaying patterns between each variable in Table 1 and each of the 9 fish biomass indicators. Because of the sheer number of graphs, we only show the mean metric of each geomorphology variable at 50-m spatial scales as examples in Appendix B. Examples of geomorphology metrics that did not display clear trends with fish biomass can be found in Appendix C.

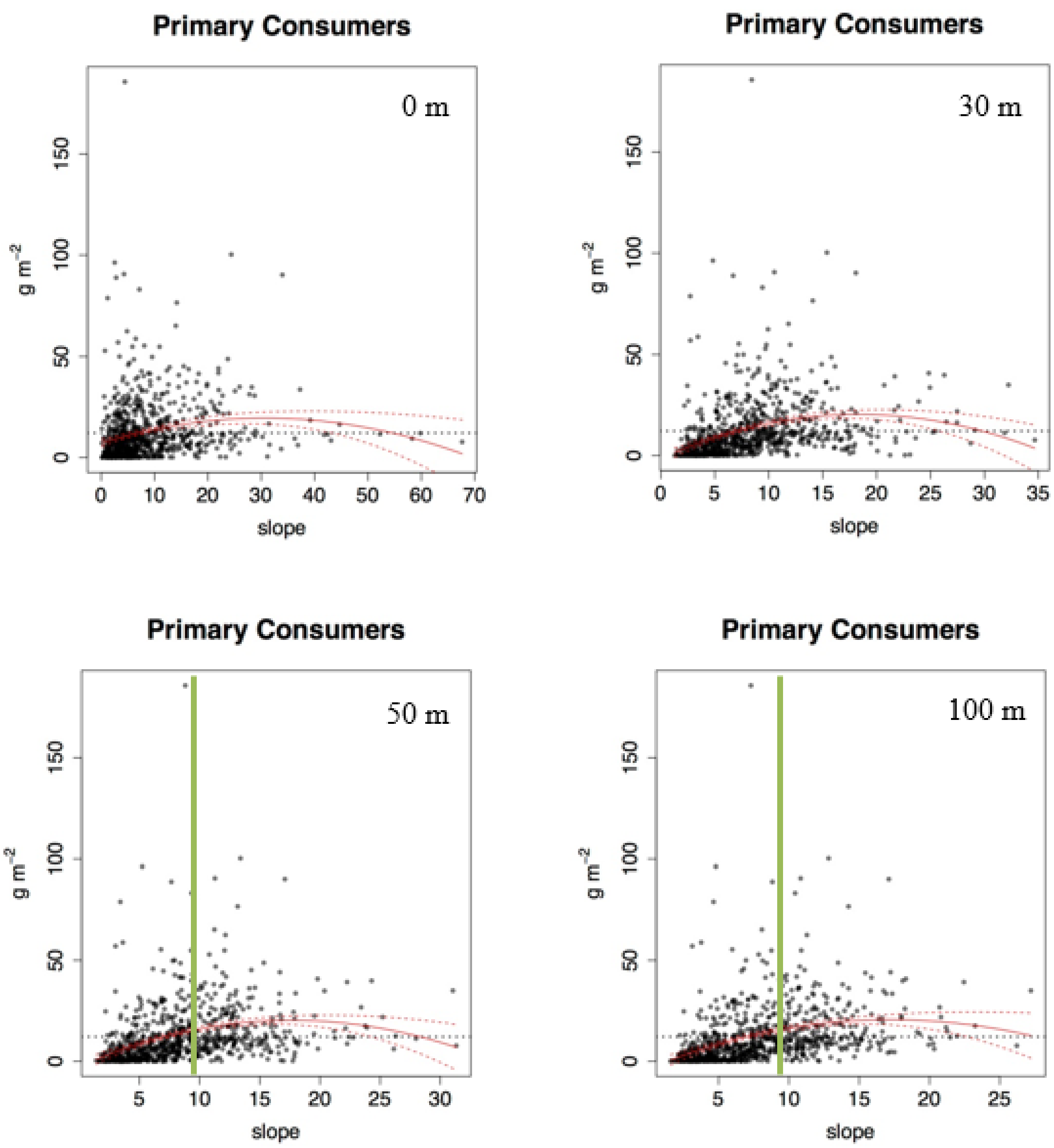


Figure 2. Slope, as an example of how for a given geomorphology, the assignment of strata bounds (green line) was consistent across different spatial scales.

Clockwise from top left: 0 m, 30 m, 100 m, and 50 m.

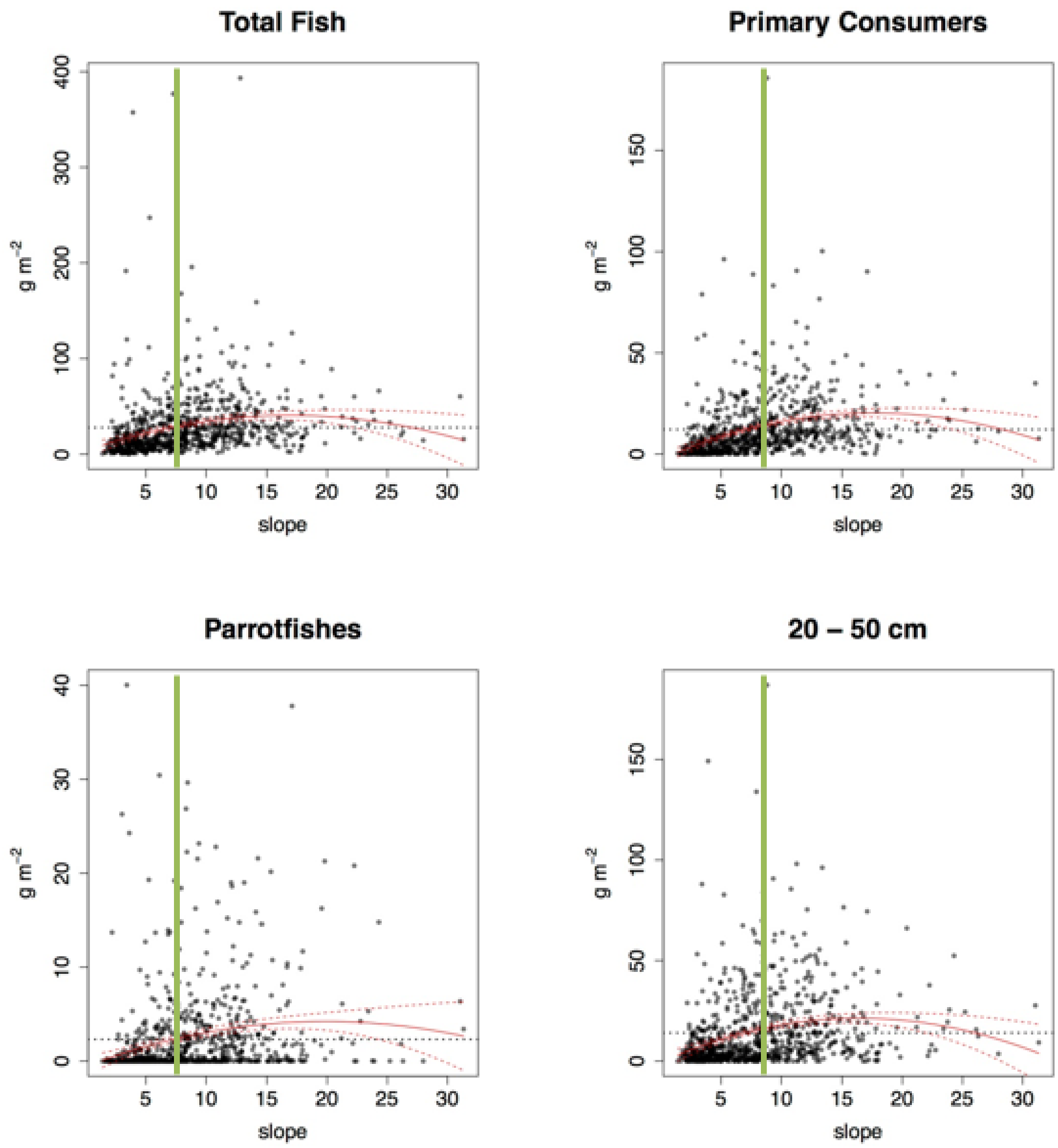


Figure 3. Slope at the 50-m scale shown as an example of how, for a given geomorphology, the assignment of strata bounds (green line) was consistent across different fish indicators.

Based on these strata boundaries, each fish survey site was assigned to a stratum based on its depth and geomorphology characteristic (i.e., post-stratification). For each stratification scheme, the number of samples (n^*) required in a future survey to achieve a CV of 20% was calculated. Next, n^* for depth only vs. depth and geomorphology stratification were compared. Overall, the geomorphology metric that resulted in the greatest reduction in n^* (i.e., the stratification scheme with the most efficient sampling) across all fish biomass indicators and across all islands was standard deviation of profile curvature at the 50-m scale (Table 4). Finally, the most efficient sampling scheme for each fish biomass indicator is listed in Table 5.

Table 4. A comparison of n* (CV = 20%) for depth only vs. depth and standard deviation of profile curvature at 50 m for various fish biomass indicators and four main Hawaiian Island complexes.

Total sample reduction was calculated as the difference in n* between depth only vs. depth and profile curvature summed across all islands.

Indicator	Stratification Scheme	Hawaii	Kauai	Maui Nui	Oahu	Total Sample Reduction
Total Fish	Depth Only	11.82	26.96	30.39	26.73	12.62
	Depth + Profile Curvature	11.56	21.00	29.25	21.46	
Primary	Depth Only	14.70	25.10	34.65	39.52	19.37
	Depth + Profile Curvature	13.75	18.21	30.11	32.54	
Secondary	Depth Only	21.44	20.73	32.34	23.17	21.09
	Depth + Profile Curvature	18.97	16.39	24.13	17.10	
Planktivore	Depth Only	44.17	52.22	111.79	86.93	27.36
	Depth + Profile Curvature	43.34	45.43	108.93	70.05	
Piscivore	Depth Only	47.56	38.77	52.22	74.64	17.45
	Depth + Profile Curvature	40.52	28.09	52.29	74.84	
0–20 cm	Depth Only	18.57	16.33	27.10	24.32	5.18
	Depth + Profile Curvature	14.87	15.85	28.21	22.22	
20–50 cm	Depth Only	19.48	25.67	37.91	46.89	19.43
	Depth + Profile Curvature	19.56	21.38	30.98	38.59	
50 cm+	Depth Only	98.14	36.21	124.35	117.78	136.41
	Depth + Profile Curvature	67.71	25.88	77.30	69.18	
Parrots	Depth Only	46.68	46.73	61.15	104.35	58.49
	Depth + Profile Curvature	41.50	28.26	59.90	70.75	

Table 5. A list of geomorphology metrics and spatial scales found to produce the greatest total sample reduction across all islands for individual fish biomass indicators.

Indicator	Optimal Geomorphology Strata	Total Sample Reduction
Total Fish	Mean Slope of Slope at 100 m	13.85
Primary	Profile Curvature Standard Deviation at 50 m	19.37
Secondary	Profile Curvature Standard Deviation at 100 m	22.67
Planktivores	Mean Slope at 50 m	39.95
Piscivores	Mean Slope of Slope at 0 m	24.45
0–20 cm	Profile Curvature Standard Deviation at 30 m	6.42
20–50 cm	Mean Slope of Slope at 100 m	19.88
50+ cm	Profile Curvature Standard Deviation at 100 m	140.83
Parrotfishes	Profile Curvature Standard Deviation at 50 m	58.49
OVERALL	Profile Curvature Standard Deviation at 50 m	317.38

Discussion

We found several geomorphological characteristics (e.g., mean slope, mean slope of slope, mean rugosity, and standard deviation of profile convexity) for a variety of spatial scales, which if added as a second stratum variable, enhanced our survey design efficiency when compared to depth-only stratification.

Slope (Pittman and Brown, 2011), slope of slope (Pittman et al., 2009), as well as remotely sensed rugosity (Kuffner et al., 2007), were found to be important predictors of fish biomass, abundance, and/or diversity in numerous other studies (Mellin et al., 2009). In our analysis, standard deviation of profile curvature produced the most efficient survey design when combined with depth stratification. As far as we know, however, this geomorphology variable has not been emphasized in previous studies of reef fish distributions.

Profile curvature (Figure 4, top row) is measured in the parallel direction of the maximum slope, while planform curvature (Figure 4, bottom row) is measured perpendicular to the direction of the maximum slope. Large values of curvature represent complex terrain, and positive or negative values are indicative of either upwardly concave or convex surface in the vertical (profile) and horizontal (planform) direction relating to slope. The importance of profile curvature standard deviation in our survey efficiency analysis indicates that variation in upwardly convex and concave environments (i.e., complex benthic terrain) may be an overlooked geomorphological variable that can aid in reef fish biomass survey design. That planform curvature was not found to be an important geomorphological variable suggests that horizontal or sideward convexity/concavity has less influence on reef fish distributions. This makes sense if one considers that reef fish distributions and the oceanographic environment, in general, are vertically as opposed to horizontally patterned.

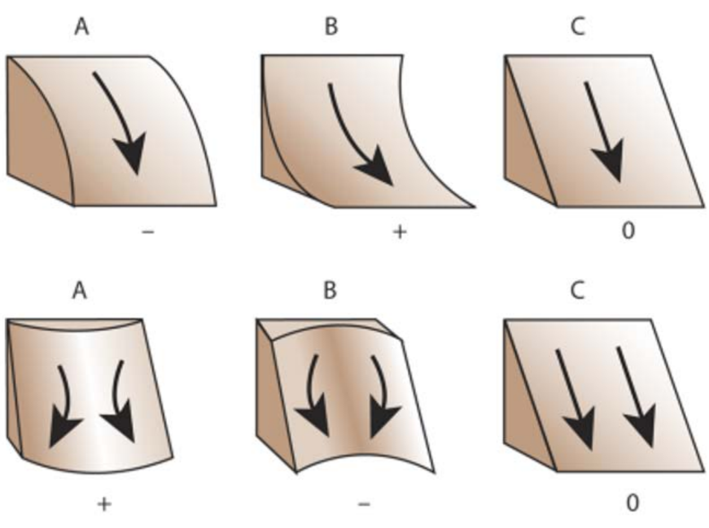


Figure 4. Top row: Illustration of profile curvature; Bottom row: Illustration of plan curvature.

Graphic credit: Esri, https://blogs.esri.com/esri/arcgis/2010/10/27/understanding-curvature-rasters/

While other studies (Chitarro, 2004) have shown that spatial scale had little influence with regard to predictive power, we found increasing predictive power with broader spatial scales. When looking at individual fish biomass indicators (Table 4), the most efficient survey designs mainly included larger (e.g., 50 and 100 m), as opposed to smaller, spatial scale predictors. 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 being among some of the confounding factors (Mellin et al., 2009).

We also demonstrate in our analysis the importance of spatial resolution when initially deriving the geomorphologies. Of the LiDAR-derived geomorphologies that were found to increase survey efficiency (i.e., mean slope, mean slope of slope, mean rugosity, and profile curvature standard deviation), none of them were found to produce the same effect when derived from coarser "synthesis" maps (see Materials and Methods). Although we used the 50-m spatial scale to calculate sampling efficiency (i.e., n^*) for each of our candidate geomorphology metrics, the original data came from much finer (i.e., 2-m) resolution LiDAR maps. Thus, even though we summarize the geomorphology metrics at a 50 m spatial scale, there is additional fine-scale information in the 2-m resolution LiDAR data that is presumably lost when we move to the 50-m "synthesis" maps.

In the future, we intend to explore more systematic possibilities for visualizing fish-geomorphology trends and determining strata boundaries. The strategy of using *loess* curves to explore overall trends in the data was mainly used as a first pass. There are likely more sophisticated techniques for exploring fish biomass trends with benthic morphology (e.g., GAMs) as well as optimization algorithms for stratifying data with the goal of lowering variance in each strata (e.g., R package *SamplingStrata*; Barcaroli 2014). Furthermore, a better test of design performance would be to derive the geomorphology stratas using a portion of the Pacific RAMP fish data set (e.g., only certain years or islands) and then testing its effect on design performance on the remaining portion. Overall, the analytical framework described here (i.e., n^* calculation) forms the basis for continuing to explore how to improve the efficiency of future reef fish monitoring efforts under Pacific RAMP.

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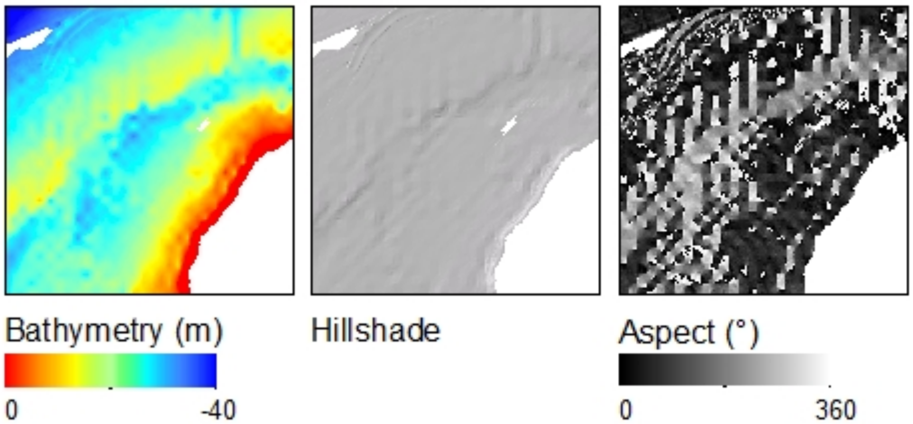
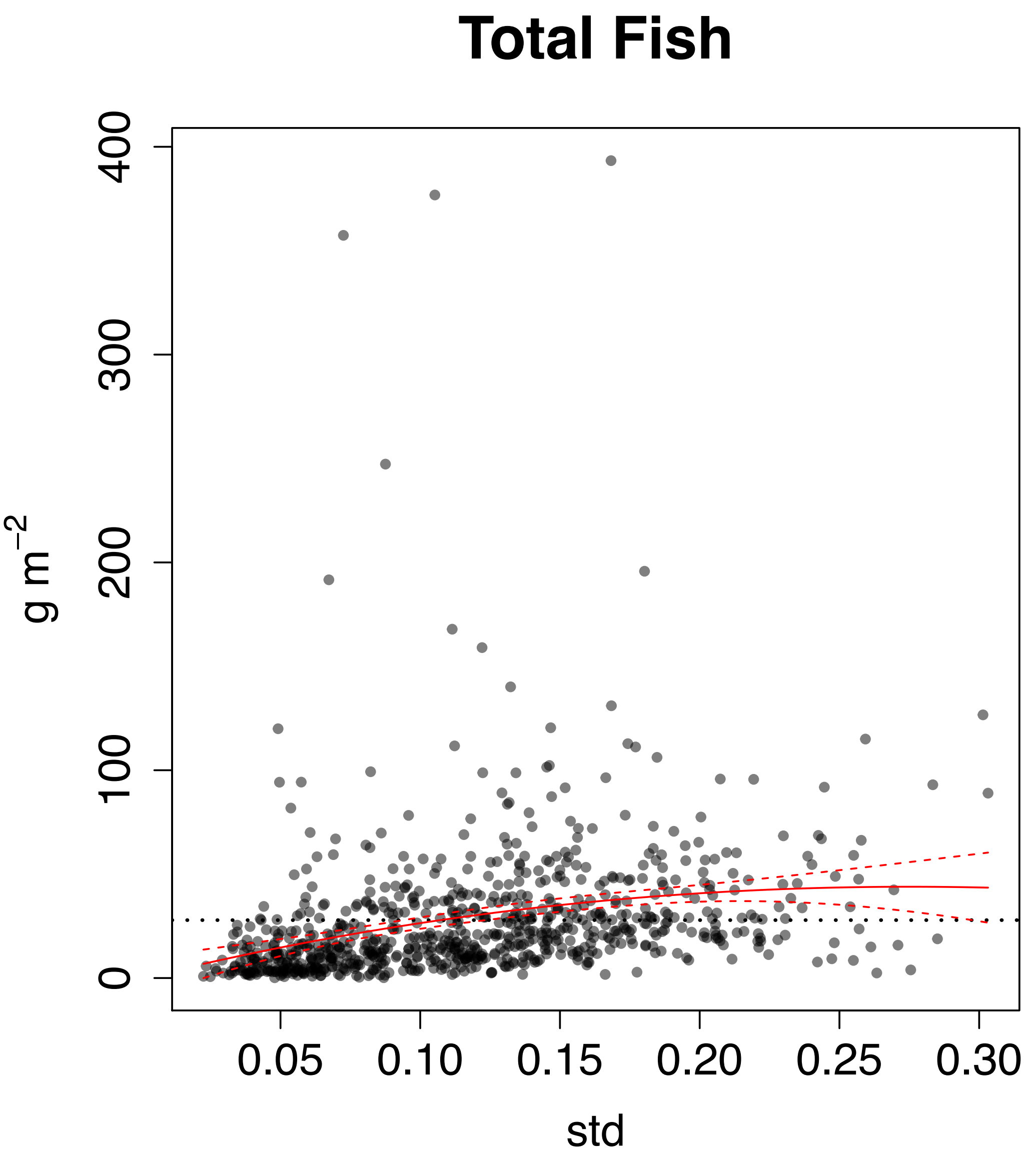
APPENDIX A – Example of distortions observed in the 5-m bathymetric data, exacerbated upon derivation of geomorphology features (the focus of this project), thus causing us to turn to other mapping data sources.

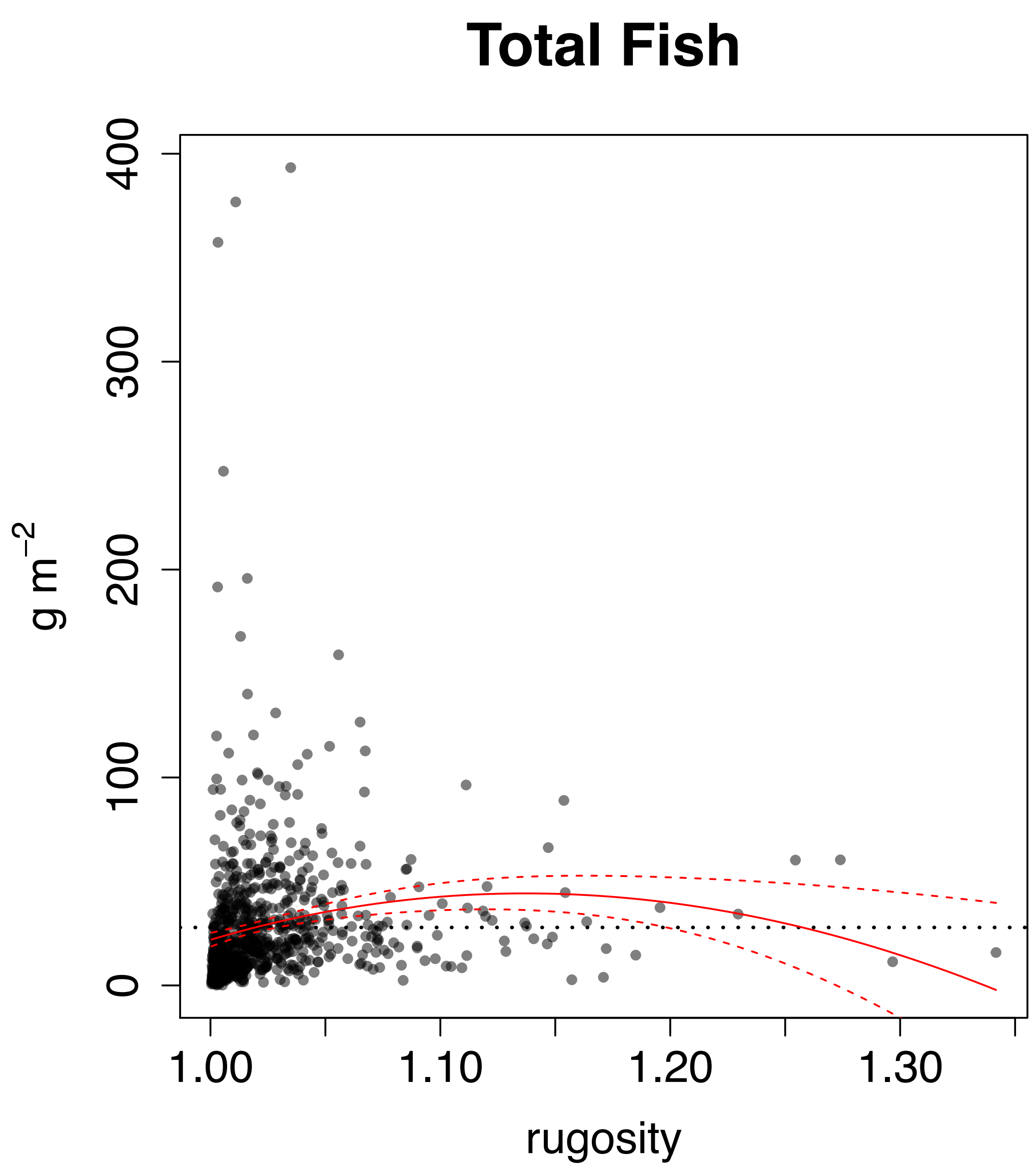


APPENDIX B – Geomorphology metrics with loess curves that trend with fish biomass (i.e., low measures of the geomorphology metric are significantly less than (based on 95% confidence intervals) the global mean for fish biomass, while high measures of the geomorphology metric are significantly greater than the global mean

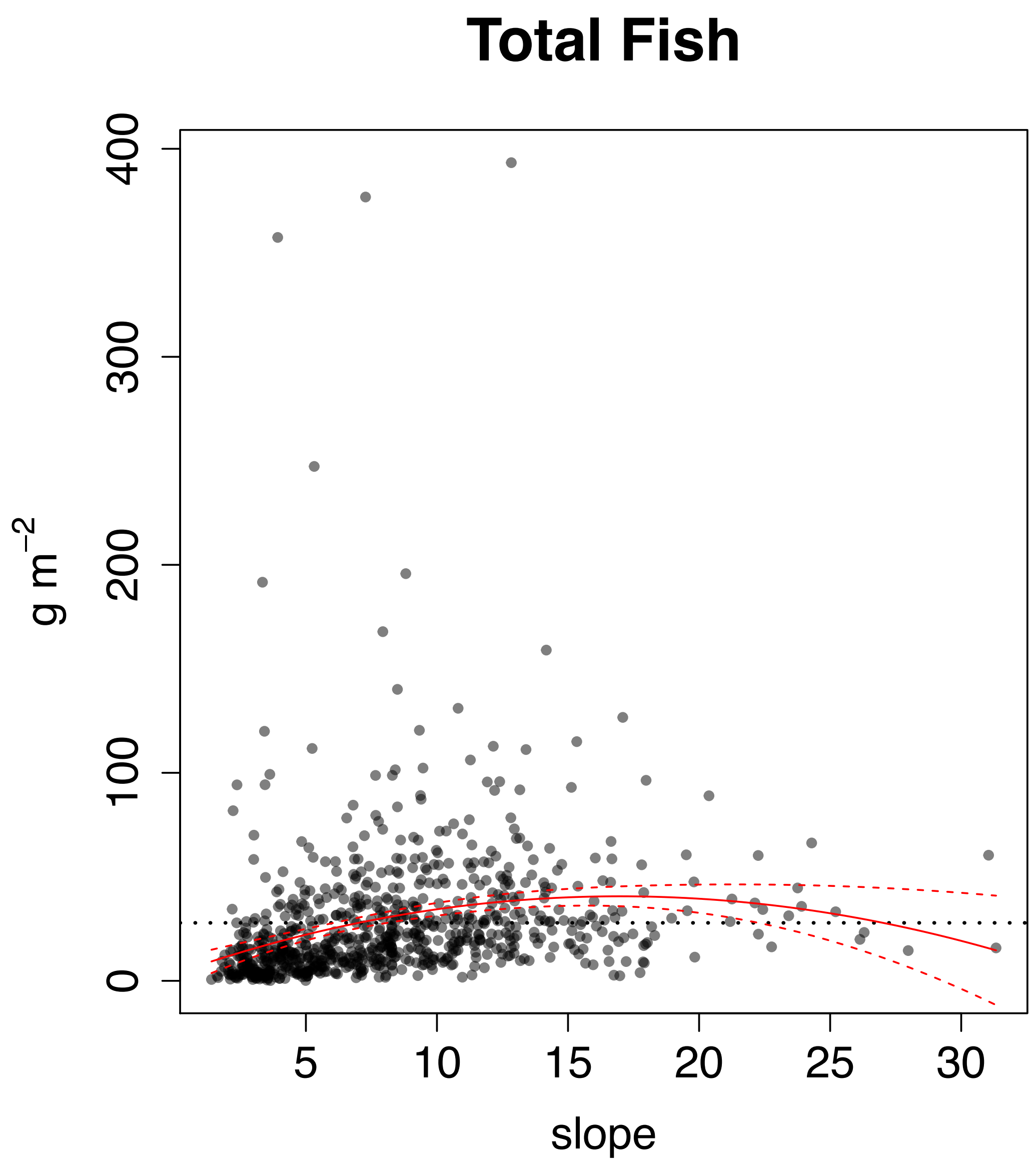
STANDARD DEVIATION OF PROFILE CURVATURE AT 50 m



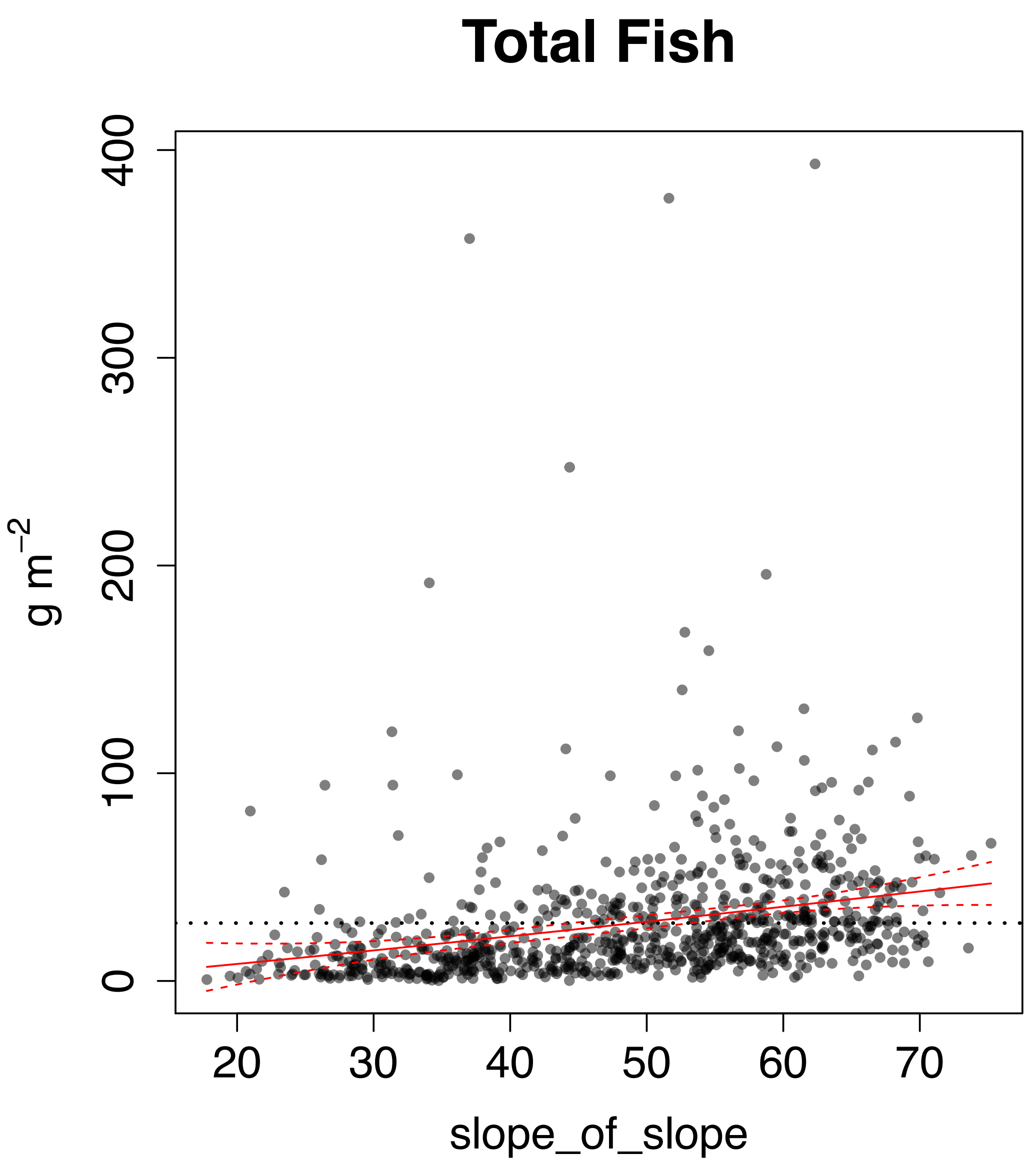
MEAN RUGOSITY AT 50 m



MEAN SLOPE AT 50 m

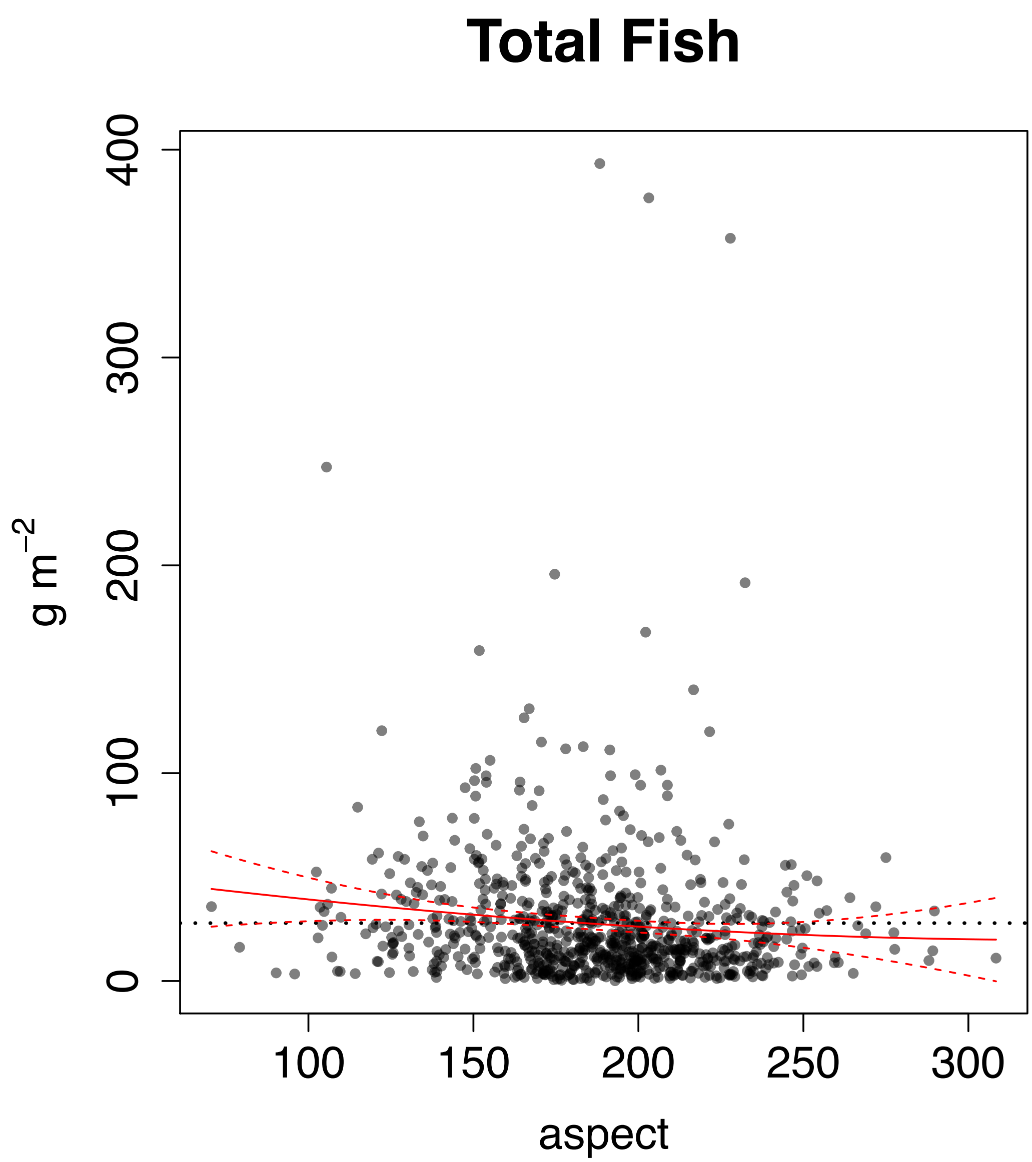


MEAN SLOPE OF SLOPE AT 50 m

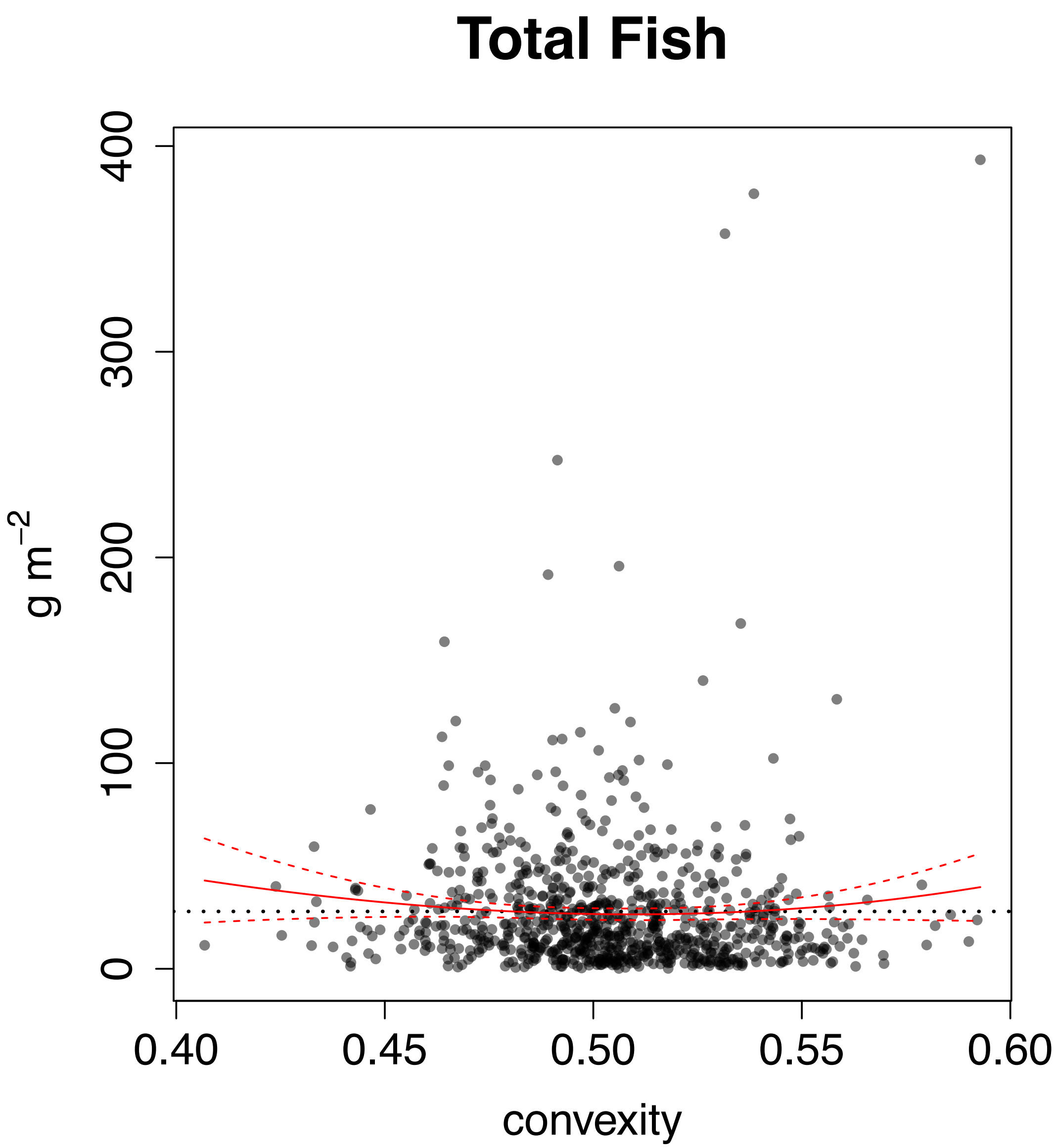


APPENDIX C – Geomorphology metrics with loess curves that show no significant trend with total fish biomass based on loess curves whose 95% confidence intervals overlap with the global mean for fish biomass throughout the full range of biomasses.

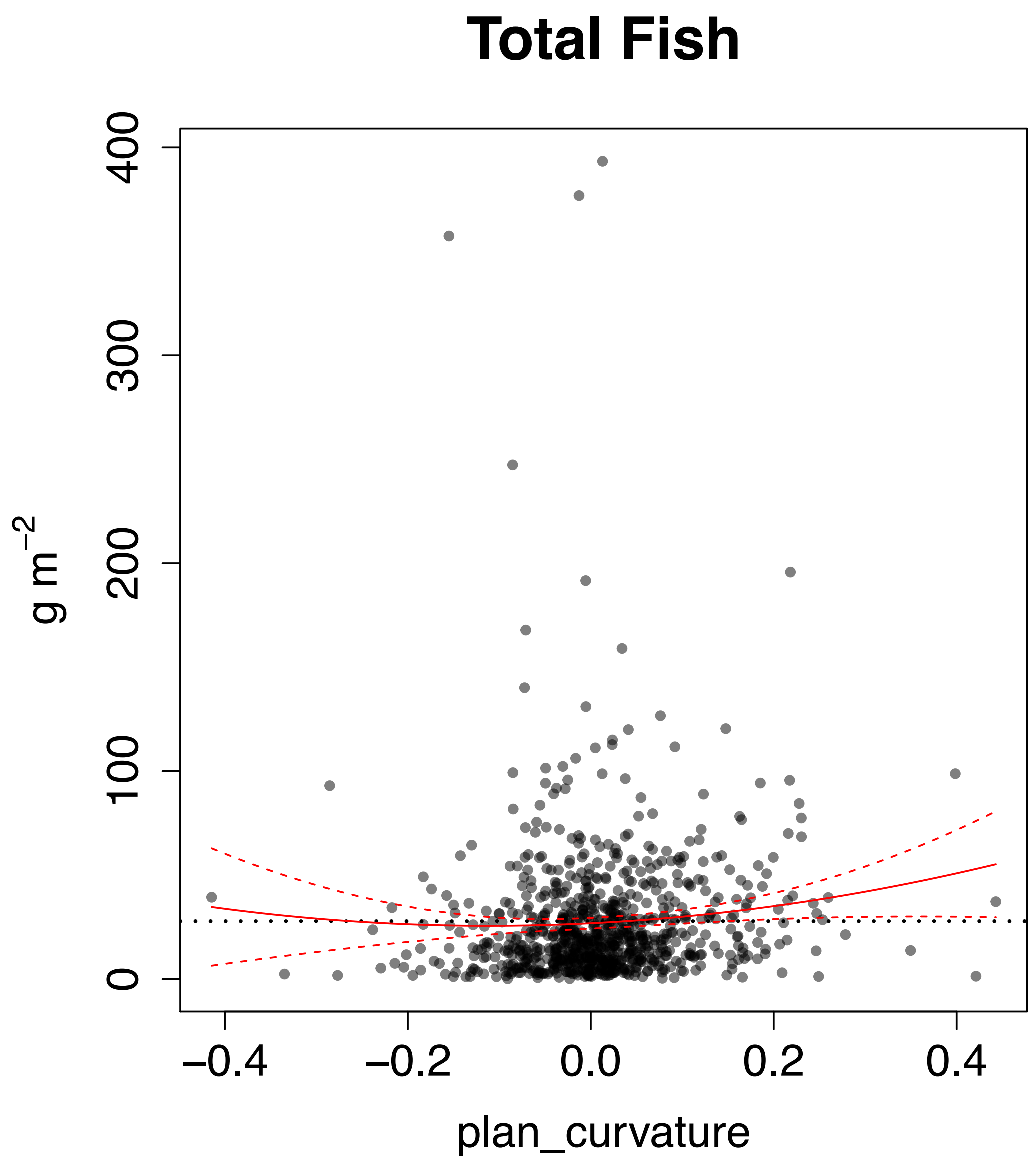
MEAN ASPECT AT 50 m



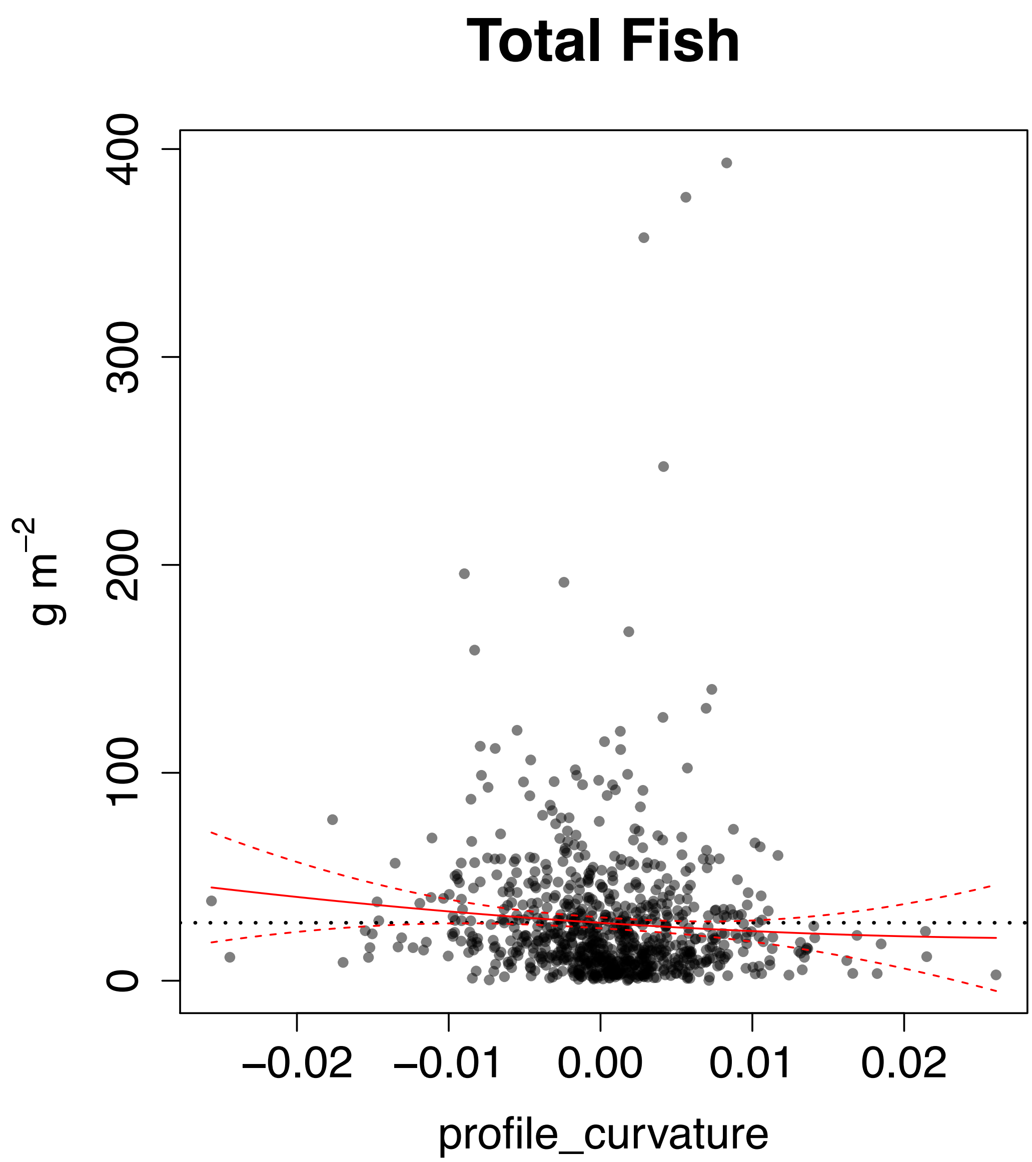
MEAN CONVEXITY AT 50 m



MEAN PLANAR CURVATURE AT 50 m



MEAN PROFILE CURVATURE AT 50 m



MEAN SURFACE AREA AT 50 m