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## Using bathymetric lidar to define nearshore benthic habitat complexity: Implications for management of reef fish assemblages in Hawaii

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### ABSTRACT

Habitat complexity plays a major role in determining the distribution and structure of fish assemblages in the aquatic environment. These locations are critical for ecosystem function and have significant implications for conservation and management. In this study, we evaluated the utility of remotely sensed lidar (light detection and ranging) data for deriving substrate rugosity (a measure of habitat complexity) on a coral reef in Hawaii. We also assessed the potential application of lidar data for examining the relationship between habitat complexity and Hawaiian reef fish assemblage characteristics. Lidar-derived rugosity (4 m grid size) was found to be highly correlated with *in-situ* rugosity and was concluded to be a viable method for measuring rugosity in analogous coral reef environments. We established that lidar-derived rugosity was a good predictor of fish biomass and demonstrated a strong relationship with several fish assemblage metrics in hard bottom habitat at multiple spatial resolutions. This research demonstrates (i) the efficacy of lidar data to provide substrate rugosity measures at scales commensurate with the resources and their environment (ii) the applicability of lidar-derived rugosity for examining fish–habitat relationships on a coral reef in Hawaii and (iii) the potential of lidar to provide information about the seascape structure that can ultimately be used to prioritize areas for conservation and management.

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### 1. Introduction

Habitat complexity in the coastal environment plays an important role in structuring nearshore fish assemblages. The relationship between habitat complexity and measures of community structure was first observed in the terrestrial realm (August, 1983; MacArthur & MacArthur, 1961; Murdoch et al., 1972; Rosenzweig & Winakur, 1969). A similar relationship between habitat complexity and fish assemblage characteristics has been well documented in both freshwater (Gorman & Karr, 1978) and marine ecosystems (Caley & St John, 1996; Friedlander & Parrish, 1998; Gratwicke & Speight, 2005; Luckhurst & Luckhurst, 1978; Risk, 1972; Roberts & Ormond, 1987).

Structural complexity, a major component of habitat complexity, can be defined as the architecture of the physical environment (McCoy & Bell, 1991; Sebens, 1991). Structurally complex habitats offer more potential niches and increase survivorship by providing fish additional refuge from predation (Almany, 2004; Beukers & Jones, 1998; Hixon & Beets, 1989). Accordingly, areas of high structural complexity harbor

high species richness (Gratwicke & Speight, 2005), species diversity (Almany, 2004) and fish biomass (Friedlander & Parrish, 1998).

There are a number of habitat complexity variables that can be measured *in-situ* (reviewed in McCormick, 1994), and rugosity is the most commonly used *in-situ* measure. For the purposes of this study, rugosity, or vertical relief, was used to represent a measure of structural complexity. The chain transect method measures *in-situ* rugosity by obtaining the ratio of the length of a chain laid across the bottom profile along a transect line to the linear distance of the transect line (Friedlander & Parrish, 1998; Luckhurst & Luckhurst, 1978; Risk, 1972). A limitation of the traditional chain transect method is the restriction of the structural complexity measurements to relatively fine spatial scales. Additionally, field measurements are time-consuming, can have high inter-observer variability, and are difficult to obtain over a broad geographic area.

Considering the documented importance of the relationship between rugosity and fish assemblage structure, it is critical to develop faster methods of determining rugosity in the marine environment at broader geographic extents. The current expansion and wide application of remote sensing technology on coral reef ecosystems were recently reviewed (Mumby et al., 2004). Lidar (Light detection and ranging) is an active remote sensor that allows for spatial analysis of structurally complex habitats (Lefsky et al., 2002).

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Lidar has recently been applied to map coral reef structure (Storlazzi et al., 2003), and to measure reef rugosity (Brock et al., 2004, 2006). Lidar can provide measurements that may be scaled to allow for extraction of information at spatial extents that are more appropriate for coral reef ecosystems and related management actions. Applying remote sensing techniques that can rapidly identify structurally complex habitat may greatly assist resource managers in locating areas that are important to protect and sustain nearshore fish populations.

The goals of this study were (1) to determine whether lidar technology can provide effective rugosity measures on a coral reef in Hawaii and (2) to examine the relationship between reef fish assemblage characteristics and lidar-derived rugosity.

## 2. Data and methods

### 2.1. Study area

The study area is located in the Hanauma Bay Marine Life Conservation District (MLCD) on the south shore of the island of Oahu, in the Hawaiian Archipelago (Fig. 1). Hanauma Bay MLCD was designated as the first “no-take” marine protected area (MPA) in Hawaii in 1967 and encompasses approximately 41 ha. This area receives over one million visitors per year and is the most visited MPA in the world (Friedlander et al., in review). The bay was formed by the collapse of two volcanic craters, with the seaward opening of the bay most likely the result of wave erosion. There are extensive coral reef and sandy-bottom habitats throughout the MPA, providing a wide range of structural complexity and habitat types. Hanauma Bay represents a unique location to examine the relationship between a relatively intact fish assemblage and its associated habitat

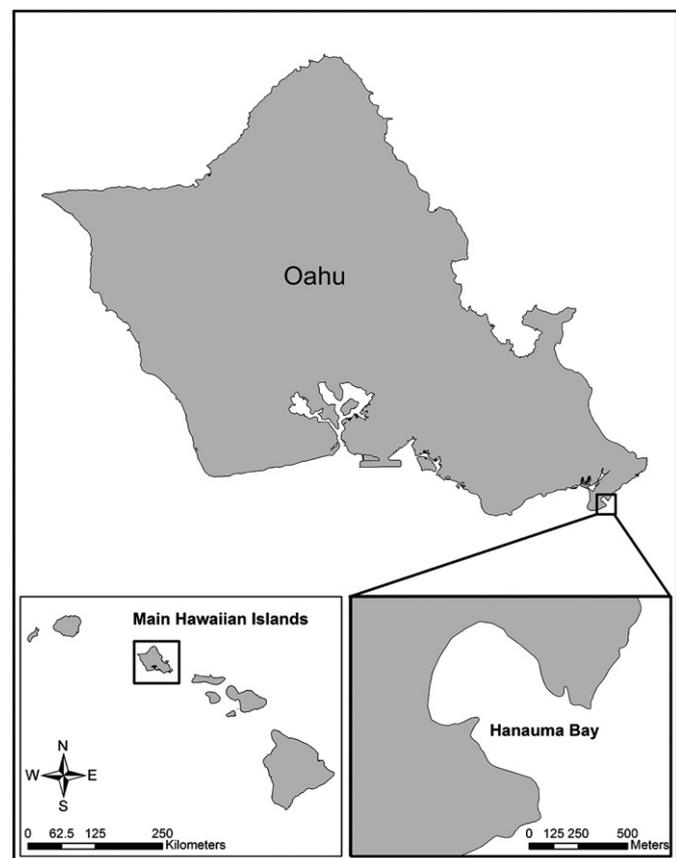


Fig. 1. Location of the study area, Hanauma Bay Marine Life Conservation District on the island of Oahu. Hanauma Bay was the first “no-take” marine protected area in Hawaii designated in 1967, and encompasses approximately 41 ha.

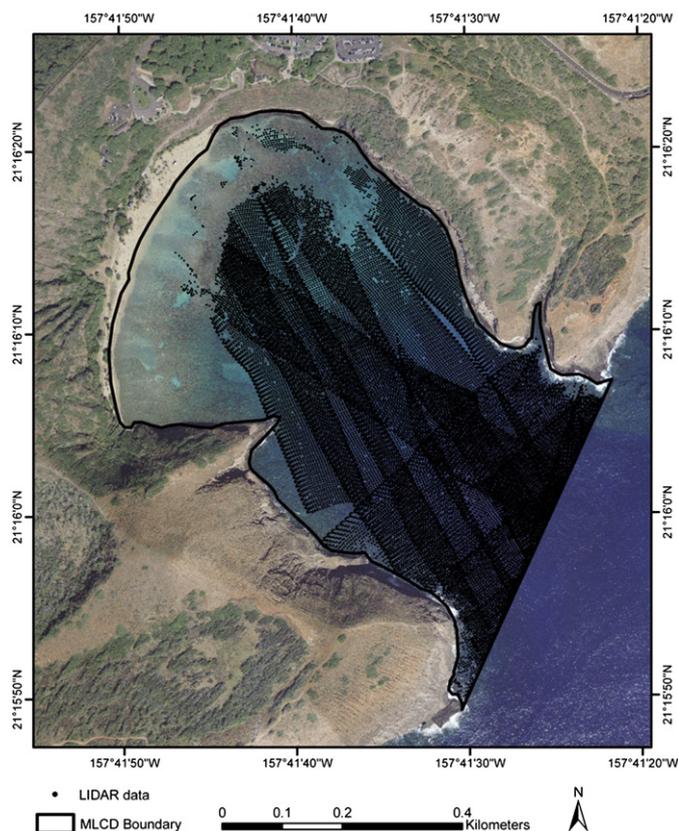


Fig. 2. U.S. Army Corps of Engineers SHOALS lidar data for Hanauma Bay Marine Life Conservation District (MLCD). MLCD boundary is denoted by the bold black line.

because fishing has been prohibited at this site for approximately forty years.

### 2.2. Lidar data

The U.S. Army Corps of Engineers SHOALS (Scanning Hydrographic Operational Airborne Lidar Survey) system is an airborne lidar bathymeter utilized to remotely collect topographic and bathymetric measurements using infrared (1064 nm) and blue-green (532 nm) scanning laser pulses. SHOALS typically operates at an altitude of 200 m allowing for a horizontal spot density of 4 m with a vertical accuracy of  $\pm 20$  cm and a horizontal accuracy of  $\pm 1.5$  m (Irish & Lillycrop, 1999). The minimum depth detection for the SHOALS sensor is typically less than 1 m, with a maximum depth detection of approximately 40 m in locations with optimal water clarity. The SHOALS lidar sensor accuracy and system performance capabilities have been summarized in detail by several authors (Guenther et al., 2000; Irish & Lillycrop, 1999; Irish & White, 1998).

SHOALS lidar data was collected in Hawaii between 1999 and 2000. A total of 38,743 lidar depth measurements were collected at the study site, but did not cover the entire bay. The shallow, nearshore areas with depths of 0.0–1.5 m and portions of the reef crest had data gaps, most likely due to the SHOALS sensor performance limitations in shallow water, where wave action and turbidity might have been present during data collection (Fig. 2).

### 2.3. Fish assemblage data

Field surveys were conducted at 33 transects in Hanauma Bay during May 2004 using a stratified random sampling design. The habitat strata [sand (UCS), colonized (CHB) and uncolonized hard bottom habitats (UCH)] were based on NOAA's Biogeography Branch benthic habitat maps (Table 1, Fig. 3) (Coyne et al., 2003). This

**Table 1**  
Number of transects performed and total area of each benthic habitat type in Hanauma Bay

| Benthic habitat type    | Code | No. of transects | Hectares |
|-------------------------|------|------------------|----------|
| Colonized hard bottom   | CHB  | 12               | 20.22    |
| Uncolonized hard bottom | UCH  | 10               | 7.12     |
| Sand                    | UCS  | 11               | 9.77     |
| Total                   |      | 33               | 37.11    |

Habitat types were based on NOAA benthic habitat maps and used for stratified random sampling of fishes and benthos. ([http://ccma.nos.noaa.gov/ecosystems/coralreef/main8hi\\_mapping.html](http://ccma.nos.noaa.gov/ecosystems/coralreef/main8hi_mapping.html)).

stratified random sampling methodology has been used in other coral reef fish studies (Appeldoorn et al., 2003; Christensen et al., 2003; Friedlander et al., 2003) to guide the sampling design and account for variation in fish abundance that may be influenced by the benthic substrate present at the site.

Fish assemblages were assessed using standard underwater visual belt transect survey methods (Brock, 1954, 1982). A diver swam a 25 by 5 m transect at a constant speed and identified to the lowest possible taxon all fishes visible within 2.5 m to either side of the centerline (125 m<sup>2</sup> transect area). Total length of fish was estimated to the nearest centimeter.

#### 2.4. In-situ rugosity

Rugosity was measured using a brass chain (1.3 cm per link) that was draped along the profile of the centerline of each 25 m transect (Friedlander & Parrish, 1998; Risk, 1972). Care was taken to ensure that the chain followed the profile of all natural fixed surfaces directly below the transect centerline. The ratio of length of the chain draped across the bottom profile to the linear distance of the transect line gave an index of rugosity.

### 3. Data analysis

#### 3.1. Lidar data processing

Digital elevation models (DEMs) are commonly produced from lidar data in order to calculate habitat structural complexity (Knudby et al., 2007). DEMs of Hanauma Bay were created at four grid cell sizes (4, 10, 15 and 25 m grids) from the lidar data using GS<sup>+</sup> (Gamma Design Software). Conditional simulation was used to create the digital elevation models. Conditional simulation is a geostatistical method that assumes spatial autocorrelation of the data and creates random realizations that possess the statistical properties of the sample data (Dungan, 2002). The DEMs were exported as grid files so that benthic terrain analysis could be completed in a GIS environment.

#### 3.2. Benthic terrain analysis

Each bathymetric DEM was analyzed using the “Benthic Terrain Modeler Tool for ArcGIS”, an ArcGIS (ESRI) tool that was created for spatial analysis of multibeam data sets, and provides a measure of rugosity from the bathymetric grids (Lundblad, 2004; Lundblad et al., 2006; Rinehart et al., 2004). This tool has been utilized to create rugosity maps from bathymetric data to inform marine resource management efforts in Fangatele Bay National Marine Sanctuary, American Samoa (Lundblad, 2004; Lundblad et al., 2006; Wright, 2002a,b).

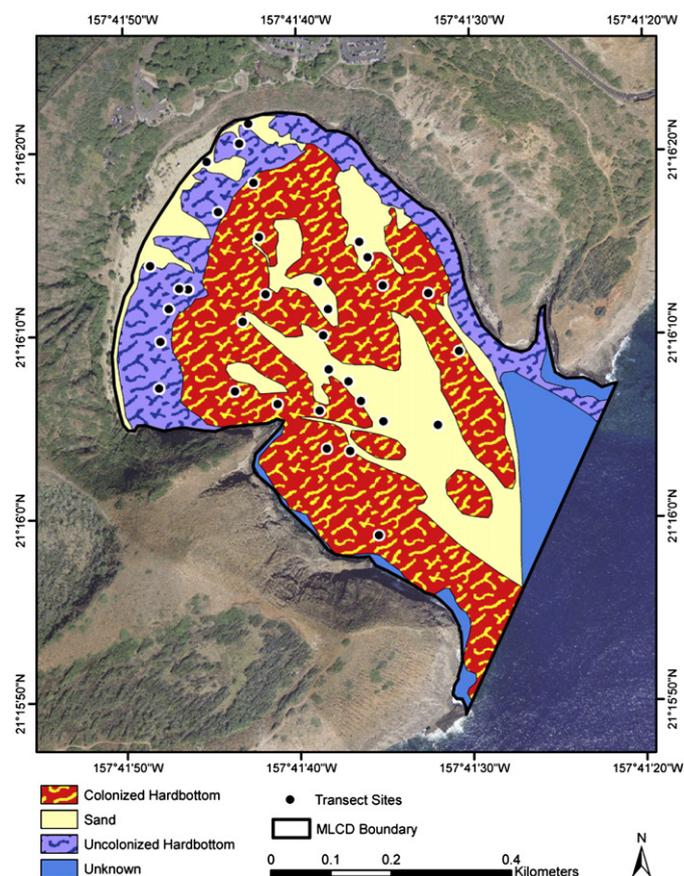
The rugosity at a transect location was derived by obtaining the ratio of the seascape surface area to the planimetric area in a neighborhood analysis for all of the grid sizes (Jenness, 2003, 2004; Lundblad et al., 2006). Transects located in areas that lacked lidar coverage were not included in any further statistical analysis because no measure of rugosity could be calculated. As a result, lidar-derived

rugosity values were obtained for twenty-two transects. The correlation between the lidar-derived rugosity (4, 10, 15 and 25 m grids) and *in-situ* rugosity was tested using the nonparametric Spearman Rho correlation coefficient (Siegel & Castellan, 1988).

#### 3.3. Association between rugosity and fish assemblages

##### 3.3.1. Fish assemblage characteristics

Numerical abundance, species richness, species diversity, and biomass were calculated to characterize the fish assemblage. Numerical abundance represented the total number of fishes on transects. Species richness was based on the total number of fish species documented on each transect. Species diversity was calculated from the Shannon–Weaver Diversity Index (Ludwig & Reynolds, 1988):  $H' = -\sum (p_i \ln p_i)$ , where  $p_i$  is the proportion of all individuals counted that were of species  $i$ . Length estimates of fishes from visual censuses were converted to weight using the following length–weight conversion:  $W = aSL^b$ , where the parameters  $a$  and  $b$  are constants for the allometric growth equation and  $SL$  is standard length in millimeters and  $W$  is weight in grams. Total length was converted to standard length by multiplying standard length to total length-fitting parameters obtained from FishBase ([www.fishbase.org](http://www.fishbase.org)). Length–weight fitting parameters were available for 150 species commonly observed on visual fish transects in Hawaii (Hawaii Cooperative Fishery Research Unit unpublished data). This was supplemented with information from other published and web-based sources. In the cases where length–weight information did not exist for a given species, the parameters from similar bodied congeners were used. All biomass estimates were converted to metric tons per hectare ( $t\ ha^{-1}$ ) to facilitate comparisons with other studies in Hawaii.



**Fig. 3.** NOAA benthic habitat map and transect locations in Hanauma Bay Marine Life Conservation District. The benthic habitat map was created using a minimum mapping unit of 0.4 ha.

3.3.2. Relationship between in-situ rugosity and fish assemblages

In-situ rugosity did not conform to the assumptions of normality despite transformation, so the correlations between measures of the fish assemblage (numerical abundance, richness, diversity and biomass) and in-situ rugosity were therefore tested using the nonparametric Spearman Rho correlation coefficient (Siegel & Castellan, 1988).

3.3.3. Relationships between lidar-derived rugosity and fish assemblages

The association between fish assemblage characteristics and rugosity was first analyzed within habitats (UCS, UCH, CHB), with data from all transects pooled. Biomass was  $\ln(x+1)$  transformed prior to regression analysis to conform to the assumptions of normality and homogeneity of variance (Zar, 1999). A least-squares simple linear regression was utilized to evaluate the relationship between fish biomass ( $t\ ha^{-1}$ ) and lidar-derived rugosity at multiple spatial resolutions. No other fish assemblage characteristics (numerical abundance, richness, diversity) conformed to the assumptions of normality despite transformation.

3.3.4. Associations between lidar-derived rugosity and fish assemblages in hard and soft bottom habitats

The relationship between fish assemblage characteristics and rugosity was analyzed by hard and soft bottom habitats. We did this to ensure that the difference in habitat alone was not inducing a relationship between lidar-derived rugosity and fish assemblage characteristics. The major habitat types used in this analysis were hard bottom (UCH, CHB) and sand (UCS). The UCH and CHB habitats were combined into hard bottom because the UCH habitat had a sample size of three and these habitats were structurally similar (Friedlander et al., 2006). When the fish data were broken down by two major habitat types, it did not conform to the assumptions of normality despite transformation. So all fish assemblage data

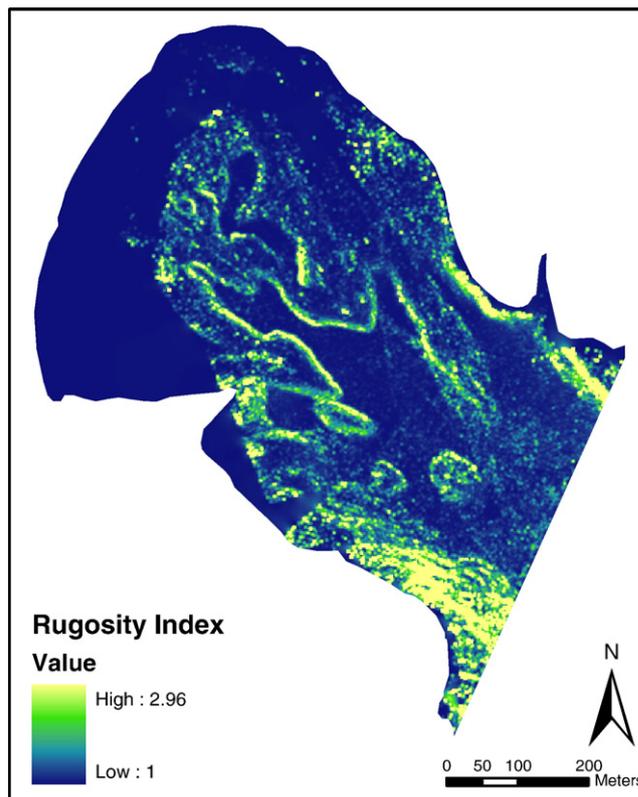


Fig. 5. Rugosity index map created from bathymetric grid using the benthic terrain modeler. Lidar-derived rugosity was calculated by obtaining the ratio of seascape surface area to the planimetric area in a neighborhood analysis.

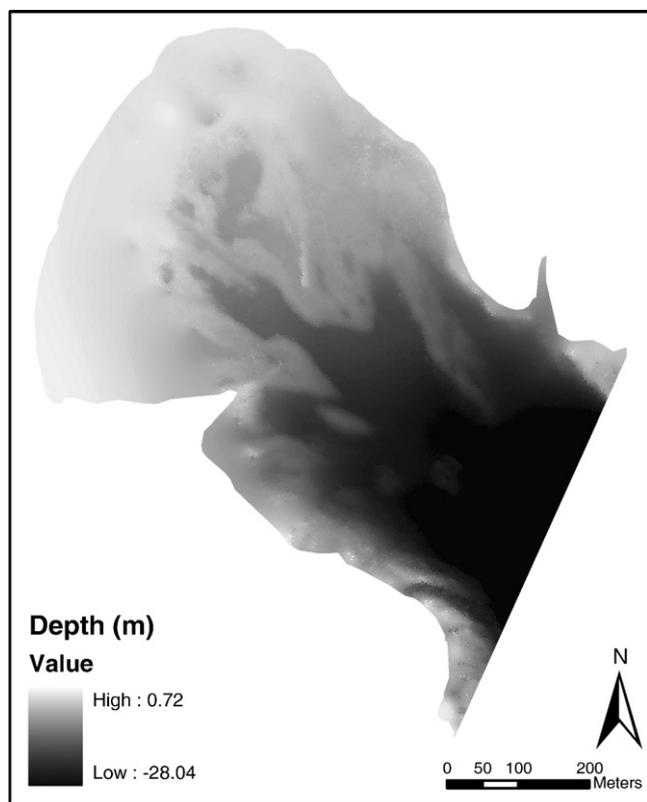


Fig. 4. Bathymetric map of Hanauma Bay created from SHOALS lidar data. Bathymetric grid was produced using the geostatistical method of conditional simulation.

(numerical abundance, richness, diversity, and biomass) were analyzed using the nonparametric Spearman Rho correlation coefficient (Siegel & Castellan, 1988) to examine the association between measures of the fish assemblage and lidar-derived rugosity by hard bottom and sand habitat.

4. Results

4.1. Benthic terrain analysis

Bathymetric grids were created at four spatial resolutions from the lidar data (Fig. 4) and rugosity values were derived from the rugosity index maps for each grid size (Fig. 5). The result of the Spearman rank correlations demonstrated that the lidar-derived rugosity at the 4 m grid size had a significant positive association ( $r=0.61, P<0.01$ ) with the in-situ rugosity, but the 10, 15, and 25 m grid sizes did not show statistically significant associations (Table 2).

4.2. Association between rugosity and fish assemblages

4.2.1. Relationship between in-situ rugosity and fish assemblages

In-situ rugosity demonstrated strong positive correlations with abundance ( $r=0.70, P<0.001$ ), diversity ( $r=0.73, P<0.001$ ), richness ( $r=0.73, P<0.001$ ), and biomass ( $r=0.49, P<0.05$ ) (Table 3).

| Grid size | 4 m                    | 10 m         | 15 m         | 25 m         |
|-----------|------------------------|--------------|--------------|--------------|
|           | <b>0.61 (&lt;0.01)</b> | -0.01 (0.98) | -0.12 (0.60) | -0.09 (0.70) |

Values denote Spearman rank correlation coefficient with P-values in parenthesis. Statistically significant correlations ( $P<0.05$ ) are shown in bold.

**Table 3**  
Correlation between *in-situ* rugosity and fish assemblage characteristics

| Numerical abundance     | Species diversity ( $H'$ ) | Species richness        | Biomass ( $t\ ha^{-1}$ ) |
|-------------------------|----------------------------|-------------------------|--------------------------|
| <b>0.70 (&lt;0.001)</b> | <b>0.73 (&lt;0.001)</b>    | <b>0.73 (&lt;0.001)</b> | <b>0.49 (&lt;0.05)</b>   |

Values denote Spearman rank correlation coefficient with  $P$ -values in parenthesis. Statistically significant correlations ( $P < 0.05$ ) are shown in bold.

**4.2.2. Relationships between lidar-derived rugosity and fish assemblages**

Results of least-squares linear regression demonstrated that lidar-derived rugosity was a statistically significant predictor of fish biomass at all grid sizes (Table 4). The lidar-derived rugosity at the 4 m grid size demonstrated the highest  $R^2$  value ( $R^2 = 0.64$ ,  $P < 0.001$ ), followed by the 10 m grid ( $R^2 = 0.46$ ,  $P < 0.001$ ), 15 m grid ( $R^2 = 0.40$ ,  $P < 0.01$ ), and 25 m grid ( $R^2 = 0.39$ ,  $P < 0.01$ ).

**4.2.3. Associations between lidar-derived rugosity and fish assemblages in hard and soft bottom habitats**

Lidar-derived rugosity demonstrated the strongest positive correlation with numerical abundance at the 25 m grid size ( $r = 0.73$ ,  $P < 0.01$ ) followed by the 4 m grid ( $r = 0.68$ ,  $P < 0.01$ ), 15 m grid ( $r = 0.67$ ,  $P < 0.01$ ), and 10 m grid ( $r = 0.58$ ,  $P < 0.05$ ) (Table 5). Species richness had a strong positive correlation with lidar-derived rugosity at the 25 m grid size ( $r = 0.66$ ,  $P < 0.01$ ), 10 m grid ( $r = 0.65$ ,  $P < 0.01$ ), 4 m grid ( $r = 0.64$ ,  $P < 0.05$ ), and the 15 m grid size was not statistically significant ( $r = 0.51$ ,  $P = 0.06$ ), but suggestive of a relationship. Fish biomass also demonstrated the strongest positive correlation with lidar-derived rugosity at the 25 m grid size ( $r = 0.65$ ,  $P < 0.05$ ), followed by the 15 m grid ( $r = 0.61$ ,  $P < 0.05$ ). The fish biomass relationships with the 4 m grid ( $r = 0.52$ ,  $P = 0.06$ ) and 10 m grid ( $r = 0.50$ ,  $P = 0.07$ ) were not statistically significant. Species diversity was not significantly correlated with lidar-derived rugosity at any grid size ( $P > 0.05$  for all).

In the sand sites, the Spearman rank correlation showed a significant negative correlation between numerical abundance and lidar-derived rugosity at the 25 m grid size ( $r = -0.69$ ,  $P < 0.05$ ). The relationships between all other measures of the fish assemblage and the 4, 10, 15 and 25 m grid sizes in the sand sites were not statistically significant.

**5. Discussion**

**5.1. The utility of lidar to provide effective rugosity measures on a coral reef in Hawaii**

Lidar-derived rugosity (4 m grid size) was found to be highly correlated with *in-situ* rugosity and represents a viable method for measuring rugosity in analogous coral reef environments. The lidar-derived rugosity in our study represented an area-based measurement, and the chain method used *in-situ* was a linear measurement of habitat complexity. Despite the fact that these two methods used in our study were measuring habitat complexity using different

**Table 4**  
Results of simple linear regression analysis with lidar-derived rugosity (4, 10, 15 and 25 m grid sizes) as the independent variable and fish biomass ( $t\ ha^{-1}$ ) as the dependent variable

| Regression statistics | 4 m                | 10 m                | 15 m                | 25 m                |
|-----------------------|--------------------|---------------------|---------------------|---------------------|
| Model: $y = bx + a$   |                    |                     |                     |                     |
| $b \pm SE$            | 14.988<br>(2.497)  | 41.380<br>(9.994)   | 49.645<br>(13.674)  | 67.761<br>(19.115)  |
| $(P >  t )$           | <0.001             | <0.001              | <0.01               | <0.01               |
| $a \pm SE$            | -14.779<br>(2.531) | -41.212<br>(10.054) | -49.492<br>(13.746) | -67.609<br>(19.188) |
| $(P >  t )$           | <0.001             | <0.001              | <0.01               | <0.01               |
| $R^2$                 | 0.643              | 0.462               | 0.397               | 0.386               |
| Error $df$            | 21                 | 21                  | 21                  | 21                  |
| Power                 | 0.998              | 0.950               | 0.889               | 0.887               |

Biomass was  $\ln(x + 1)$  transformed before the analysis.

**Table 5**  
Correlation between lidar-derived rugosity and fish assemblage characteristics in hard bottom habitat

| Grid size                  | 25 m                   | 15 m                   | 10 m                   | 4 m                    |
|----------------------------|------------------------|------------------------|------------------------|------------------------|
| Numerical abundance        | <b>0.73 (&lt;0.01)</b> | <b>0.67 (&lt;0.01)</b> | <b>0.58 (&lt;0.05)</b> | <b>0.68 (&lt;0.01)</b> |
| Species richness           | <b>0.66 (&lt;0.01)</b> | 0.51 (0.06)            | <b>0.65 (&lt;0.01)</b> | <b>0.64 (&lt;0.05)</b> |
| Biomass ( $t\ ha^{-1}$ )   | <b>0.65 (&lt;0.05)</b> | <b>0.61 (&lt;0.05)</b> | 0.50 (0.07)            | 0.52 (0.06)            |
| Species diversity ( $H'$ ) | 0.41 (0.14)            | 0.21 (0.45)            | 0.51 (0.06)            | 0.41 (0.14)            |

Values denote Spearman rank correlation coefficient with  $P$ -values in parenthesis. Statistically significant correlations ( $P < 0.05$ ) are shown in bold.

approaches, the results demonstrated a strong relationship and support the findings of several previous studies. For instance, earlier work by Luckhurst and Luckhurst (1978) concluded that their *in-situ* area-based measurements were highly correlated to linear measurements of habitat complexity. A strong relationship between *in-situ* area-based and linear measurements of habitat complexity has also been documented by Friedlander and Parrish (1998). Further, Kuffner et al. (2007) applied an area-based measure of rugosity to a lidar-derived DEM and found this to be significantly correlated to the *in-situ* linear measure of rugosity obtained using the chain method.

The *in-situ* chain method is limited to relatively fine spatial scales but coral reefs demonstrate habitat complexity at a range of spatial scales (Hatcher, 1997), from centimeters to kilometers. *In-situ* rugosity was only significantly correlated with lidar-derived rugosity at the 4 m grid, and this may be a result of the fine spatial scale, and smaller geographic extent, that was represented by the 4 m DEM. The lidar-derived rugosity was calculated from the DEM in the GIS environment for a single grid cell by using the values of the 8 surrounding grid cells. As a result, the 4 m grid size DEM represented an extent of 144 m<sup>2</sup> for the rugosity analysis. In contrast, the 25 m grid size DEM represented a much broader extent of 5625 m<sup>2</sup>. The lidar-derived rugosity, calculated at the 10, 15 and 25 m grid sizes, was representing coral reef complexity at a broader geographic extent that did not correlate with the complexity measures obtained at the fine spatial scale and small geographic extent of the chain method.

Although the lidar-derived rugosity measured at broader spatial scales (10, 15 or 25 m grid size) did not have a significant relationship with *in-situ* rugosity, these measures of habitat complexity represent relevant information for reef fish studies using a landscape ecology approach. Landscape ecology commonly focuses on the ecological effects (i.e. species distribution, movement and persistence) of spatial pattern in the landscape at broad geographic extents (Turner, 1989). Therefore, lidar-derived rugosity (10, 15 or 25 m grid size) may not be an appropriate alternative to the chain method at these resolutions, but has the potential to be applied for the purpose of studying fish-habitat relationships at broad geographic extents that are more relevant to resource management actions.

Measurements derived from *in-situ* methods are limited by SCUBA diving time and depth constraints, as well as shoreline and boat access to study sites. Lidar has potential as an improved method for determining habitat complexity because it can provide relevant information about the coastal habitat across a broad geographic area in a minimal amount of time. However, there are a number of deployment issues that may be involved including the remoteness of the study site and the cost associated with the proximity to areas of interest. When considering the use of this type of remotely sensed data for research and management purposes the cost to collect and process lidar data should be taken into account.

**5.2. Relationship between lidar-derived rugosity and reef fish assemblage structure**

A number of authors have established that *in-situ* rugosity plays an important role in structuring fish assemblages (Friedlander & Parrish, 1998; Gratwicke & Speight, 2005; Luckhurst & Luckhurst, 1978; Risk, 1972; Roberts & Ormond, 1987). Our results clearly show that rugosity,

measured using a well established field method, has a strong association with all measures of the fish community at our study area. This provided the basis for the evaluation of the relationship between lidar-derived rugosity and measures of fish assemblage structure collected at the same study area.

Hard bottom sites demonstrated significant associations with lidar-derived rugosity and numerical abundance (4, 10, 15, 25 m grid), richness (4, 10, 25 m grid), and biomass (15, 25 m grid). The 25 m grid cell size (5625 m<sup>2</sup>) showed the strongest correlation for all three assemblage metrics we measured. Recent work by Purkis et al. (2008) also found a strong relationship between satellite-derived habitat complexity and fish metrics at a similar, broad geographic extent of 5030 m<sup>2</sup>. It should be noted that both studies were completed in areas with little to no fishing pressure.

The fish assemblage within the MPA boundary at our study site was found to harbor eight times the biomass, and had a much greater number of large-bodied resource species, compared with adjacent fished areas (Friedlander et al., 2006, 2007a,b). This is significant because large-bodied fishes often have larger home ranges (Holland et al., 1993; Meyer et al., 2007) and seek shelter commensurate with their body size (Friedlander & Parrish, 1998). For instance, the home range size of the giant trevally (*Caranx ignobilis*), a highly mobile predator that can reach a maximum size of 165 cm, ranged on average from 5 to 9 km, with occasional movements up to 29 km away from core areas (Lowe et al., 2006; Meyer et al., 2007). In contrast, Meyer and Holland (2003) studied movement in the bluespine unicornfish (*Naso unicornis*), a smaller-bodied surgeonfish ( $\bar{X}=47$  cm), that demonstrated daily movement patterns less than 1 km. The exploitation of larger refuge holes and habitat utilization across a broader geographical extent by fishes in Hanauma Bay may explain why our study found that fish assemblage organization was responding to habitat complexity measures at a broad geographic extent (25 m grid cell size=5625 m<sup>2</sup>).

When examined alone, regardless of the resolution, sand sites were not well correlated with fish assemblage characteristics. Sand habitats often function as corridors between the structurally complex reef habitats and, as a result, fish transiting these locations are highly variable and not easily surveyed. In addition, sand habitats show little to no variability in habitat complexity so it is not surprising that fish assemblage structure is not correlated. Although lidar had limited utility in the sand habitats, results have shown the importance of these corridors as transit pathways among hard bottom habitats or as important feeding locations (Friedlander et al., 2007a). As a result, lidar should be integrated with benthic habitat maps to help explain assemblage structure and habitat use patterns.

We concluded that lidar-derived rugosity was a good predictor of fish biomass in Hanauma Bay. This finding extends previous work by Kuffner et al. (2007), who found that lidar-derived rugosity measured from a 1 m DEM, using varied window sizes, was a statistically significant, but weak predictor of coral reef fish species richness in Florida. This previous work was conducted in patch reef habitat that contained a limited range of habitat complexities, and, therefore, may have not been representative of ecological relationships at the ecosystem level. Several distinct habitat types in a contiguous reef environment were incorporated in our study and this allowed for the relationship of the fish assemblage to be explored across a broad range of habitat complexities.

### 5.3. Implications for management of reef fish assemblages

Coral reef fishes demonstrate habitat utilization patterns across the seascape (Appeldoorn et al., 2003; Christensen et al., 2003), and the presence of structurally complex habitat may provide refuge from predation and increased survivorship as fish move between habitat types (Pittman et al., 2007a). An MPA should protect a range of structural complexity and habitat types in order for fisheries enhancement goals to be reached (Sladek Nowlis & Friedlander,

2004). The ability to predict fish assemblages across a range of benthic habitat types represents an important step in allowing managers to properly plan effective marine protected areas (Valesini et al., 2004).

Remotely sensed data can predict the fisheries potential of an area (Purkis et al., 2008) and support optimal location and design of marine protected areas (Monaco et al., 2007) by identifying specific areas that offer great natural protection through structural complexity. We established that lidar-derived rugosity was a good predictor of fish biomass at all spatial scales examined. Several other studies have used broad scale measures of habitat complexity to predict coral reef fish assemblage metrics, such as species richness (Pittman et al., 2007b), diversity and abundance (Purkis et al., 2008). Purkis et al. (2008) noted stronger predictions from satellite data in larger-bodied fishes. This is important to consider as fisheries management goals often involve the protection of larger female fish inside MPA boundaries (Palumbi, 2004; Sladek Nowlis & Friedlander, 2005). Larger fishes are valuable because they are more fecund, and produce viable offspring (Berkeley et al., 2004). If remote sensing provides data on habitat complexity at a scale most relevant to the larger-bodied fishes the application of the predictive species mapping may be ideal for selecting optimal sites for fisheries replenishment and MPA design. The relationships between lidar-derived rugosity and fish assemblage structure should be established at other locations in Hawaii so that more robust predictive mapping can be used to identify potential sites for future MPAs. The next step is to scale-up this approach to see if these same fish–habitat relationships exist elsewhere in Hawaii, and to determine if lidar-derived rugosity can be used to predict fish assemblage structure and ultimately prioritize areas for conservation and management.

## 6. Conclusions

The first goal of this study was to determine whether lidar technology could provide effective rugosity measures on a coral reef in Hawaii. Lidar was found to provide valuable rugosity measures at our study site and our findings extend prior work in Florida patch reefs (Brock et al., 2004; Kuffner et al., 2007) to a contiguous coral reef environment in Hawaii. The second goal of this study was to examine the relationship between reef fish assemblage characteristics and lidar-derived rugosity. An important step in applying lidar technology for resource management applications is relating the lidar-derived rugosity to various fish assemblage characteristics. We determined that lidar technology can be utilized to study the ecological role of habitat complexity on a coral reef in Hawaii. The results of our study suggest that lidar-derived rugosity may be used as a surrogate for various measures of fish assemblage structure, and this suggests that lidar data has the potential to assist in prioritizing areas for conservation and management. Expanding this work across the Main Hawaiian Islands will allow us to see if remotely sensed lidar data will provide relevant information at geographic scales commensurate with resource management efforts across the state of Hawaii.

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