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IDENTIFICATION AND CHARACTERIZATION OF SAND DEPOSIT
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By

Christopher L. Conger

Thesis Committee:

Charles H. Fletcher, Chairperson
Neil Frazer
John Rooney
Eric Hochberg
We certify that we have read this thesis and that, in our opinion, it is satisfactory in scope and quality as a thesis for the degree of Master of Science in Geology and Geophysics.

THESIS COMMITTEE

Chairperson

[Signatures]

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CHAPTER 1

INTRODUCTION

Carbonate sand on the sea floor is an important component of the geology and ecology of nearshore fringing reefs on Oahu, Hawai’i. Sands also play a key role as a dynamic influence on bathymetry through their interplay with hydrologic environmental conditions. These sands are a product of direct sedimentation from nearshore and reef top organisms, and mechanical erosion of reefal carbonates, which are created, stored, and transported across the reef top environment. Thus sand distribution is a function of organic and mechanical production, hydrologic environment, reef ecology, geomorphology, and geology. My goal is to identify patterns of sand deposit distribution to better understand the role of sand within the coastal environment and how its presence is controlled by the same environment.

This thesis is the product of combined work in remote sensing, data analysis, geology, reef ecology, and geomorphology, all aimed at improving understanding of carbonate sandy substrate on high volcanic islands. By studying sandy substrate in a local (Oahu, Hawai’i) setting, I have developed methods that can be exported to other marine settings.

There are five chapters within this thesis. The first chapter is this general introduction. The second, third and fourth chapters are each manuscripts dealing with different portions of research on sand identification, classification, and analysis. The fifth chapter contains conclusions on how these avenues of research have aided in understanding sand distribution.
Chapter 2 outlines a neural network classification algorithm as applied to the supervised identification of sandy substrate, both subaerial and submarine. This is a useful technique in small regional settings where water quality is close to homogenous and very clear. We used data from Gezirut Siyal to explore the utility of artificial neural network (ANN) classification algorithms for sandy substrate identification across nearshore marine and subaerial coastal regions. Under these conditions an ANN classifier achieves very high classification accuracies for identifying sands on slopes dipping in directions spanning all points on the compass and in both marine and subaerial environments. This technique was our first successful step in automating, with increased speed and accuracy, the sand identification process, which allowed us to begin prospecting for nearshore sands across larger regions.

Chapter 3 is a unique method for fusing LIDAR bathymetry and Quickbird color bands to remove the effects of light attenuation in the water column. Once these effects are removed it is possible to discriminate carbonate sands from other marine substrates by supervised classification algorithms or a band intensity threshold tool. This technique, more accurately and efficiently than any other, allows us to map carbonate sands on the reef top across large regions with heterogeneous water properties.

Chapter 4 applies the method presented in Chapter 3 to the fringing reef of Oahu, Hawai‘i, to produce a supervised classification for sand deposits, their geologic significance, and their distribution patterns. Finally, Chapter 4 identifies five general reef types for the study area, and describes their geologic and environmental characteristics; as well as discusses their applicability to other reefs. This chapter analyzes and interprets
the locations and shapes of carbonate sand deposits, and relates these to hydrologic environment, geology, and geomorphology for Oahu's fringing reefs.

Chapter 5 concludes the thesis with a summary of my research and its application to improved understanding of nearshore carbonate sands on the reef top. Included in this discussion are caveats and recommended uses for the methods.
CHAPTER 2
ARTIFICIAL NEURAL NETWORK CLASSIFICATION OF SAND IN ALL VISIBLE 
SUBMARINE AND SUBAERIAL REGIONS OF A DIGITAL IMAGE

2.1 INTRODUCTION

Shallow marine sand is an important resource, an integral component of the reef 
system, and a highly dynamic substrate. Currently there is a dearth of information 
concerning sand in each of these roles. As a result, our understanding of shallow marine 
sand changes through time and our ability to manage sand as a resource are not optimal. 
Inexpensive, efficient, and accurate image products that track sand spatial distribution 
and temporal variability are significant assets for improving understanding of sand 
dynamics.

Many available remotely sensed data sets, like aerial photographs, do not provide 
the high spectral resolution needed to separate multiple information classes. However, 
when identifying the monotonic signature of sand, multiple classes are not necessary. 
Most substrate classifications of digital imagery rely on either ground truth data to 
generate training classes, or a library of identified spectral returns, or both. These 
methods require analysts to either collect field data, or acquire hyper/multi-spectral 
imagery, or both. Here, we develop a simple method to classify shallow sandy substrate 
without the aid of ground truth data, a spectral library, or hyper/multi-spectral imagery. 
The goal of this analysis was to minimize cost while remaining entirely remote during 
analysis of the image.
To achieve these goals we use analyst-derived training classes to define an artificial neural network (ANN) that models a three band dataset comprising blue (470 nm), green (550 nm) and a third band consisting of the second eigenchannel (Lyzenga, 1978; Rencher, 2002; Richards and Jai, 1999) of a Principal Component Analysis of the blue and green wavelengths. Terrestrial image analysts have successfully used ANN classification programs in various environments (Egmont-Peterson et al., 2002; Mohanty and Majumdar, 1996). They have high success rates with models that apply basic classifications to the digital image (Serpico et al., 1996). It is our intent to generate an ANN that queries for the simple presence or absence of sand, thus refining for marine application, techniques previously used in terrestrial settings.

2.2 STUDY SITE

Gezirat Siyul is a roughly triangular island formed by a shore-detached reef platform along the Egyptian coast of the Red Sea. The island has limited vegetation, and is almost exclusively sand in composition. The south end is ~700 m in length, the east end is ~850 m in length, and the west end is marked by a deep lagoon along its 1020 m length. A shallow sand and gravel bar extends north of the island. A wide fringing reef and large sand field extend seaward from east, west, and north sides of the island but vary in morphology (Figure 2.1). This site was chosen because of the quality of CASI imagery, nearly homogeneous water quality, small overall area, and diversity of nearshore morphologies.
2.3 METHODS

2.3.1 Initial Data

Hyperspectral data of Gezirat Siyul and surrounding waters were acquired with 1 m pixel resolution on 3 April 2000. The data were processed in a four band format containing geo-rectified, 8 bit, pixel interleaved information for bands at 470 nm, 550 nm, 608 nm, and 850 nm.

We utilized the 470 nm and the 550 nm bands from the processed image data. Bands at both 608 nm and 850 nm did not register returns for any significant depth below sea level, and consequently, were not included in our analysis. To begin identifying differences in bottom type we applied a Principal Components Analysis and used the second eigenchannel from these two bands. The transformed data highlight features not evident in the original image (Richards and Jai, 1999). Analysis of the images determined that the first eigenchannel was dominated by changes in bathymetry, while variation in the second eigenchannel was more closely related to diversity in the bottom types, though not accurately enough to classify the image. For input values for the neural network we used three 8-bit channels: 470 nm, 550 nm, and the second eigenchannel.

2.3.2 Artificial Neural Network

We use the ANN provided by PCI Geomatics in the Xspace software. ANN’s are computer replications of biological systems. Input data are interlinked to a set of multiple, simple decision tools (neurons) that conduct basic operations, such as discriminant analysis or transformation by a sigmoid function, on the data before passing them forward to the next set of neurons. PCI’s ANN is a back-propagation network that
utilizes the Generalized Delta Rule for learning. This is a type of multilayer feed-forward network that adjusts the connection weights between each layer during the back-propagation process (Staff, 2003).

2.3.3 Training

We specified pixels within training classes using a polygon seeding tool that starts from a single pixel and moves outward choosing similar pixels. We chose initial seed pixels by their color and location within the image. This process requires an experienced marine geologist capable of identifying sandy substrate in remotely sensed images of submarine environments without a priori knowledge. Figure 2.1 shows the “sand” training pixels as red areas and “not sand” training areas as green pixels. Tolerance within the seeding program can be adjusted between levels 1 and 50, from most stringent to most relaxed respectively. We chose to use values between one and six to limit the cluster size of the training pixels and ensure those pixels chosen were similar to the original seed pixel. We also chose to collect small clusters of pixels from spatially well-distributed locations across the visible sea floor, the island, and exposed portions of the reef. “Sand” training class comprised 61,323 pixels or 0.67% of the image. “Not sand” training class comprised 51,120 pixels or 0.56% of the image.

Individual training pixels are fed through the network during the training portion of the program. In creating the network we chose the number of layers in the ANN, the cutoff tolerances for individual pixel errors, total normalized error, and maximum number of iterations, and the speed, or learning and momentum rates, at which the connections between the layers are adjusted. We used three layers for the network, as this
produced accurate results will minimizing computation time and complexity within the
ANN’s structure. Pixel values for each channel constitute the input layer. Initial
discrimination and conversion to a new coordinate system occur in the hidden layer. Final
discrimination and class labeling occur in the output layer.

After all training pixels have passed through the network the program conducts an
error analysis for all individual pixels and for each training group. If errors are outside of
the predetermined cutoff limits, and the maximum number of learning cycles has not
been reached, then the total normalized error for all training pixels is used by the
Generalized Delta Rule to reweight each connection during back-propagation (Clothiaux
and Bachmann, 1994). Then the next learning cycle is begun.

We used 0.001 as our maximum normalized total error, 0.005 as our maximum
individual error, and 1000 as our maximum number of learning cycles. The amount of
reweighting, or the magnitude of corrections is controlled by both the learning rate and
the momentum rate. Learning rate, between 0.1 and 1.0, controls how quickly the
network stabilizes, with high rates possibly converging early. Momentum rate, between
0.1 and 1.0, controls the step size of corrections, with high rates possibly overstepping
and preventing convergence. We chose to use moderate values of 0.6 and 0.5
respectively, which increased both computing time and accuracy.

Network training ends when one of the three preset cutoff limits is reached. If the
process is stopped because it reaches the maximum number of learning cycles, then the
analyst needs to either choose new training pixels (because the classes are not distinct
enough for the network to separate them) or choose higher tolerances for individual error
and total normalized error.
In the training portion of this algorithm each pixel generates a closeness of fit value for “sand” and “not sand” classes. The pixel is then placed into the class it most closely fits. Including all other bottom types into one class simplifies our query and allows the network to focus on a simple discrimination between sand pixels and all other pixels. Once the network has been trained to a sufficiently low error, the next important step is to ensure low error cutoffs are not the result of local error minima instead of a global error minimum (Hewitson and Crane, 1994). One method to check the model’s global accuracy is to compare its results against test pixel sets.

2.3.4 Testing

ANN testing, an empirical testing method, is accomplished by choosing test sets of pixels for each class (Zhang, 1996). Test pixel sets must not overlap training pixel sets (Kumar et al., 1997). Using the pixel seeding tool with strict tolerances between one and four allowed us to select many, small, similar packages of pixels for testing. Again, initial seed pixel selection requires an experienced marine geologist, as they are chosen according to color and location within the image. Figure 2.1 shows the test pixels. Yellow areas are “sand” test pixels and magenta areas are “not sand” test pixels. The trained ANN is exported to the test sets of pixels and their success rates for properly classifying the known pixels are recorded within a confusion matrix. This success rate, when combined with both the statistics produced from the training process error analysis and an analyst computed confusion matrix allows the analyst to assess the overall performance of the ANN. Our test set for “sand” comprised 6,222 pixels, or 10.15% the volume of the
training class. Our test set for “not sand” comprised 6,107 pixels, or 11.85% the volume of the training class.

2.3.5 Application

Once the network was trained, tested, and determined to be viable, it was exported to the entire image. The image was masked to remove all areas where the sea floor or subaerial environment was not visible (blue area in Figure 2.1). The total pixel count for the classified image is 9,174,405. Each pixel in the unmasked region was passed through the network individually and labeled as either “sand” or “not sand.”

2.4 RESULTS AND DISCUSSION

Results for creating the neural network from the training classes are displayed in Table 2.1 as a confusion matrix. Confusion matrices have two important outputs, the producer’s accuracy and the user’s accuracy. Producer’s accuracy describes error of omission (how accurately are known class members properly identified). User’s accuracy describes error of commission (how often an identified class contains known members). The user’s accuracy is most useful for this method because it is a way of quantifying how well the network identified the pixels it was presented (RICHARDS and JIA, 1999). User’s accuracy for the “sand” at 99.34%, and “not sand” at 97.17% was sufficient to warrant testing the network.

The network required 1222 learning cycles to fall beneath the limit for normalized total error. The tolerance was increased from 0.001 to 0.005 after the first 1000 learning cycles. The final normalized total error was 0.0039607 and the final maximum individual
error was 1.6830440, as seen in Table 2.1. Analysis of incorrectly identified pixels in each class indicates that margins between bright, hard-bottom substrate and sand, in shallow water, are repeatedly misclassified as “not sand.” Additionally, dark material, possibly rubble or algae covered sand, within sand fields are repeatedly misclassified as sand. Pixels for each training class are displayed in blue vs. green spectral space in Figure 2.2. The green pixels, those misclassified in both classes, are overlapping in the margin between the two classes.

Results from sending test pixels through the network are displayed in Table 2.2 as a confusion matrix. Pixels for each test class are displayed in blue vs. green spectral space in Figure 2.3. There are differences in the accuracies reported for the training and test statistics. These differences are the result of both normal variation of the image’s spectral characteristics and analyst error associated with pixel selection. Using small percentages of the classified image to create and test the classification model allows for some skewness to the results due to analyst error. However, high accuracies calculated within the confusion matrices of both training and test sets, though different, indicate a valid classification model that is ready to export to the image.

Finally the masked image, Figure 2.1, was passed through the neural network as individual pixels, and the result was a classified image (Figure 2.4). Final image classification yields class distributions of 53.78% “sand” and 46.22% “not sand.” Each pixel is approximately one square meter, thus the approximate areal coverage of “sand” is 2221 m² and “not sand” is 2059 m².
2.5 CONCLUSION

The ANN approach to image classification in shallow marine and subaerial coastal environments is particularly useful when attempting to segment the data into two broad information classes. Limited initial data consisting of red, green, and blue channels do not provide enough information to compare with hyper/multi-spectral signature libraries and requires some preclassification processing to assist in discrimination by a supervised classification model. We found Principal Component Analysis to be a useful preprocessing tool, with the first eigenchannel displaying variation resulting from bathymetric changes and the second eigenchannel displaying variation associated with substrate change. Including subaerial sand in our “sand” class and subaerial non-sand features in our “not sand” class extended the range of our neural network from submarine through subaerial environments.

There is inherent difficulty in creating a classification model that functions in both environments simultaneously while producing accurate results. Training and test pixels are chosen by the analyst without the aid of ground truth data; thus there exists a potential error for incorrect class identification and pixel labeling. Care should be taken when choosing the amount and location of both training and test pixels. For example, when sand occurs in a variety of environments, a training set that does not include sand form each environment will not accurately constrain the spectral extent of the class. In addition, each class must be adequately sampled or they may be underrepresented within the classification structure.

Use of a seeding tool with strict control on tolerance settings is critical for selecting viable training and test groups. Learning and momentum rates have a significant
impact on network accuracy, thus increased computing time resulting from lower rates is considered to be a worthwhile investment in network accuracy. Testing is an important step for validating that the error results were not a product of local error minima but rather the global error minimum, and are representative of the entire image and not just the training pixels.

ANN classification of coastal zone sandy substrate is a robust and accurate technique, however it is important to remember several issues before using this method. First, though this has worked well for coastal zone of Gezirat Siyul, a small island with almost homogenous waters, it will perform less accurately for increasingly heterogeneous waters across larger areas. Second, this technique requires very careful selection of training pixels, and repeated testing before final classification. And third, though this example (under nearly perfect environmental conditions) properly identifies sands on slopes dipping in directions spanning all points on the compass, it may not perform as well in under other environmental conditions.
CHAPTER 3

DECORRELATING REMOTE SENSING COLOR BANDS FROM BATHYMETRY

IN OPTICALLY SHALLOW WATERS

3.1 INTRODUCTION

Remote sensing has long been a useful tool for study of coastal benthic environments (reviewed in Green et al., 1996). Numerous case studies point to the ability of remote sensing technology to provide meaningful, quantitative data on ecological and geomorphological systems (Ahmed and Neil, 1994; Andréfouët et al., 2003; Atkinson and Grigg, 1984; Bina et al., 1978; Bour et al., 1986; Mumby et al., 1998; Smith, 1975). Research into the technology itself has generated practical techniques for processing aquatic remote sensing imagery (Bierwirth et al., 1993; Gould and Arnone, 1997; Hochberg et al., 2003; Lyzenga, 1978; Roelfsema et al., 2002) and for linking optical remote sensing data with biophysical sea floor parameters (Hochberg and Atkinson, 2000; Hochberg and Atkinson, 2003; Holden and LeDrew, 1998; Myers et al., 1999; Purkis and Pasterkamp, 2004). The primary hindrance to routine use of remote sensing for study of optically shallow benthic environments is the presence of a highly (relative to air) absorbing and scattering water column of variable depth (Maritorena et al., 1994). The remote sensing problem is to remove these unknown radiative transfer effects from an unknown and variable sea-floor albedo signal.

The most commonly cited approach to compensate for water column radiative transfer effects is that of Lyzenga (1978; 1981; 1985). This simple physics-based technique is derived from two-flow irradiance transfer and exploits the intrinsic
correlation between two color bands to generate a pseudo-depth and a pseudo-color band. First, for each image color band, the signal from an optically deep portion of the scene is subtracted from the entire band, and the difference is ln-transformed. This transformation has the effect of (approximately) linearizing the data with respect to depth. Next, a model 2 regression is performed on two of the ln-transformed color bands, and the bands are rotated so that the regression slope becomes the abscissa in a new coordinate system. This new abscissa is primarily related to variations in water depth, while the orthogonal ordinate axis is primarily related to variations in bottom albedo. Theoretically, the pseudo-depth channel can be calibrated with appropriate ground truth information to provide absolute depth, and the pseudo-color channel is a depth-invariant index of seafloor composition.

While it has proven to be a useful processing step (Mumby et al., 1998), there are complications associated with Lyzenga’s method. First, the computed pseudo-depth channel is dependent on the relationship between bottom albedos in the two color bands. The result is that different bottom-types at the same actual depth appear at different pseudo-depths. More importantly, since it is a rotation of a convolution of two wavebands, it is difficult to interpret a physical basis for the pseudo-color band. Advancements on Lyzenga’s basic model include the recognition that water column optical properties can be spatially heterogeneous within a scene (Tassan, 1996). Other researchers have focused on merging external bathymetry data with Lyzenga rotation results, thus providing absolute calibration for the pseudo-depth channel and creating a bathymetric chart at the resolution of the digital image data (Estep et al., 1994; Lee and Tuell, 2003; Wozencraft et al., 2003; Yarbrough and Easson, 2003).
We present a new method for decorrelating remote sensing color bands from bathymetry, inspired both by Lyzenga's rotation approach and by efforts to merge LIDAR bathymetry data with color band data. Modern LIDAR systems have the ability to generate data at meter-scale spatial resolution, which is near that of high-resolution satellite image systems such as Ikonos (4 m) and Quickbird (2.4 m). Availability of such high-resolution data removes the need for computing water depth from passive imaging data, yet there is still a need to compensate for water column radiative transfer effects in the color-band data. Our approach is to linearize color bands with respect to depth following Lyzenga's method. However, rather than rotating two color bands about the regression slope, we rotate a single color band against the high resolution bathymetry. In the resulting coordinate system, the ordinate axis represents color band data decorrelated from water depth: for a given bottom reflector-type (i.e., a constant albedo), intensity in the rotated color band is independent of water depth. We demonstrate this technique using Quickbird satellite imagery and a SHOALS LIDAR interpolated bathymetry surface.

3.2 MATERIALS AND METHODS

3.2.1 Model

For a given color band, the remotely sensed signal (less atmospheric and sea surface effects) can be modeled as a linear function of bottom albedo and an exponential function of water depth (Fig. 3.1A) (Maritorena et al., 1994). Variations from the exponential decay are due to backscattering in the water column. Taking the natural logarithm of the remotely sensed signal has the effect of (approximately) linearizing the
color band data with respect to depth (Fig. 3.1B). Computing the model 2 linear regression between the ln-transformed color band and depth, and rotating the coordinate system about that regression line decorrelates the color band data from water depth (Fig. 3.1C). In other words, by rotating the ln-transformed color band according to its linear relationship with depth, we are left with a color band whose intensity no longer decreases with increasing depth. The decorrelated color band data do not have physically meaningful units, but can be calibrated to absolute albedo using techniques such as the empirical line method. This model requires that bathymetry information exists for each pixel in the color bands.

An important component of our model is the data from which we compute the model 2 linear regression. Considering an entire coastal scene, several different bottom-types are present, represented by different bottom albedos. After linearization, these albedos form roughly parallel lines, as in Fig. 3.1B. If all bottom albedos are equally present at all depths under consideration, then a regression computed for all pixels will return the correct slope. However, if some albedos are not present, then the regression line becomes skewed toward those albedos that are present. For example, if the first several "low albedo" points in Fig. 3.1B were missing, then the regression slope would be more strongly negative. That is, variability in the data is due to both bottom composition and water optical depth. Since our goal is to remove the variability due to depth while maintaining variability due to bottom composition, it is advantageous to compute the regression line using only a single bottom reflector-type (Mumby et al., 1998) that is present throughout the scene. Then, the entire scene may be rotated about the regression line.
3.2.2 Data

We demonstrated this technique using two independent data sets for Kailua Bay, Oahu, Hawaii (Fig. 3.2A): (1) a Quickbird image acquired March 13, 2003 (scene ID 03MAR13205953), and (2) SHOALS (Scanning Hydrographic Operational Airborne Lidar Survey) LIDAR bathymetry data acquired in 1999. Three bands were used from the Quickbird image: blue (450-520 nm), green (520-600 nm), and red (630-690 nm). The Quickbird scene exhibited excellent environmental quality, with very high water clarity, few breaking waves, no visible surface gravity waves, negligible glint, and almost no cloud cover. The image was georectified with a resolution of 2.4 meters per pixel. For this study, we considered only the three visible wavebands in a 1500 x 1000 pixel subset of the image at the northern end of the Kailua Bay, extending from shore to optically deep water (Fig. 3.2B). The average distance between the irregularly spaced, non-gridded SHOALS data points was 2.8 meters. We used a continuous curvature surface gridding algorithm (Generic Mapping Tools’ surface function) to rasterize the LIDAR data, creating a bathymetric surface at the same 2.4 m pixel resolution as, and coregistered with, the Quickbird data (Fig. 3.2C). We created an image mask to remove the influence of clouds, subaerial surfaces, and artifacts in the bathymetric surface from the analyzed portion of the image, leaving 1,055,157 pixels for evaluation.

3.2.3 Processing

Following Lyzenga (1978; 1981; 1985) for each color band, we determined the minimum value from a portion of the scene covering optically deep water. We subtracted
this deep-water value from the entire color band then computed the natural logarithm. To constrain the model 2 regression, we defined a region of interest in a nearshore-to-offshore transect that encompassed 2,164 pixels of carbonate sand (a relatively homogeneous reflector), with depths ranging from near sea level to 20 m (Fig. 3.2B). Using these transect pixels, we performed a regression for each color band against corresponding depth values extracted from the SHOALS image. Since these are two-variable systems, we used Principal Component Analysis to compute the perpendicular regression coefficients (Rencher, 2002). The first principal component described the major axis of the bivariate data, which in this case represented the attenuation of signal with depth. The orthogonal second component described the minor axis of the bivariate data, in this case variations of signal within the homogeneous sand reflector-type. This second principal component provided the rotation coefficients to rotate the entire In-transformed color band, thus decorrelating it from depth. To quantify the utility of rotation, we computed the correlation of each color band with depth before and after rotation, using the transect pixels.

3.3 RESULTS

Fig. 3.3 shows the sand transect pixels for each color band plotted against depth at each processing step: initial data (Fig. 3.3A), In-transformed data (Fig. 3.3B), and rotated data (Fig. 3.3C). These graphs illustrate decorrelation in both blue and green bands, and a lack of decorrelation in the red band. Figure 3.4 shows gray scale images of each color band before and after processing. Rotation greatly enhances contrast of bottom features in the blue and green bands, while the rotated red band exhibits mostly noise. For sand
transect pixels, correlation coefficients with depth before rotation (and after In-
transformation) are 0.979, 0.991, and 0.857 for the blue, green, and red bands,
respectively. After rotation, correlation coefficients are 0.001, 0.002, and 0.012 for the
blue, green, and red bands, respectively. Rotation clearly decorrelates the blue and green
bands from water depth. While the after-rotation correlation value for the red band is
much smaller than the before-rotation correlation value, examination of Fig. 3.3C and
Fig. 3.4F reveals that rotation coefficients computed from pixels in optically deep waters
are not viable products.

3.4 DISCUSSION

Our proposed technique relies on the strong linear relationship between In-
transformed color bands and depth in optically shallow water. We have invoked a
simplified two-flow irradiance transfer model as the physical basis for this relationship.
Maritorena, et al. (1994) provide an excellent derivation of the model and clearly
demonstrate its utility for describing shallow water reflectance. To the best of our
knowledge, all case studies on the matter have found the model’s approximations to be
perfectly adequate (e.g., Bierwirth et al., 1993; Lyzenga, 1978; Mumby et al., 1998),
despite the fact that most remote sensing studies consider radiance (often in units of
digital counts) as opposed to irradiance or reflectance. It is nevertheless important to
understand that this is a one-dimensional model, describing only the vertical variation of
light within the water column, including the seafloor.

The first implication is that the atmosphere and sea surface are not included. Prior
to application of the model, compensation must be provided for non-water column
radiative transfer effects such as aerosol scattering or sun glint. Algorithms exist for such compensations (e.g., Andréfouët et al., 2001; Hochberg et al., 2003). For the image used in this study, only minor glint effects are present, and subtracting deep-water radiance from the entire scene acts as a zero-order atmospheric correction.

The second implication is that the model assumes a vertically homogeneous water column with respect to optical properties. The coastal zone is often a complex hydrodynamic environment, resulting in vertical variations of biotic and abiotic optically significant water column constituents. However, Maritorena et al. (1994) point out that it is possible to assume a "bulk" attenuation that describes the entire water column. In fact, our method does not rely on knowledge of actual attenuation values, but simply that attenuation is approximately exponential through the water column considered as a whole. Deviation from this exponential attenuation, as may occur in vertically stratified waters, has the potential to detrimentally affect the technique.

The final implication of the model is that it does not account for horizontal variation in water column optical properties. That is, we assume that attenuation is constant throughout the scene. For the present study, this is a reasonable assumption, given the excellent environmental conditions under which the imagery was acquired: the study area is small, Kailua Bay is open to the ocean, allowing significant water exchange, and neither wind nor surface gravity waves are present in the image, with no apparent sediment resuspension. However, just as optical properties vary vertically around coral reefs, they also vary horizontally across spatial scales of 10's of m to km (Karpouzli et al., 2003; Maritorena and Guillocheau, 1996). Such variability must be considered before application of this model. If significant variability is found, then the image may be
divided into subsets, each with relatively constant optical properties, or algorithms may be applied which automatically account for such variability, such as that proposed by Tassan (1996).

Another important consideration for application of this method is the depth-of-detection limit, which is the depth where the seafloor-returned signal is no longer strong enough to provide for bottom detection and/or discrimination. In this study, the linear relationship between ln-transformed color bands and depth is clearly apparent in both the blue and green, but is notably absent in the red (Fig. 3.3B). Examination of the data reveals that the blue and green bands exhibit strong seafloor-return signals (SNR ~100) to depths of 40 and 25 m, respectively, while the red band loses the seafloor signal at only 5 m depth (Fig. 3.3 and 3.4C). For most of the scene under consideration, the balance of variability in the red channel is comprised of sea surface clutter and sensor noise. Thus, it is inappropriate to apply the rotation to this channel, and the appearance of seafloor features in the rotated red band (Fig. 3.4F) is an artifact of the lack of decorrelation from the depth band.

Discounting environmental and sensor noise, variability in the color bands comes from two sources. First, and most significant, is attenuation due to water optical depth. For an homogenous bottom-type, and therefore a relatively homogenous reflector, Fig. 3.3A indicates ranges of approximately 150, 400 and 200 digital counts for the blue, green, and red color bands, respectively, across the depths considered in this study. The second source of variability arises from differences in reflector type. The green band in Fig. 3.3A shows a range of about 75 digital counts near 4 m depth, indicating local differences in sand albedo in those pixels. After rotation, Fig. 3.3C still shows this local
variation, but the global depth-dependent variation is no longer present. Thus, this technique effectively removes variations due to water depth, while maintaining variations due to bottom signal.

Removal of variation associated with water depth is possible because of the approximately linear relationship between ln-transformed reflectance and water depth, as measured by the correlation coefficient. High correlation coefficients, 0.979 and 0.991 measured for the sand pixels in blue and green ln-transformed bands respectively, indicate an almost perfect linear relationship (Fig. 3.3B). In striking contrast are the same sand pixels in the ln-transformed red band. These pixels pass into optically deep waters by 5 m, no longer varying with depth and blowing up during the ln-transform. Though by other standards these pixels’ correlation coefficient of 0.857 may seem high, in this case it is unacceptable by comparison to the almost perfect linear relationship exhibited when the bottom is in optically shallow waters. Consequently, after rotation the red sand pixels in Fig. 3.3C do not display the same narrow range of variation, resulting from minor differences in sand albedo, as do both blue and green. Fig. 3.3C is the product of pixel data in optically deep waters where the rotation coefficients are computed for sensor noise and surface clutter. Again, though a correlation coefficient of 0.012 may seem low by normal standards, in this case it is completely unacceptable.

The only discontinuity in the linear relationships of the blue and green ln-transformed sand pixels with depth is around 2 m. There is a slight steepening of the trend in this shallow region of the scene. One possible source for this discontinuity might be localized sediment resuspension from the higher energy environment of the near-shore breaker region. This would create different water column optical properties than the rest.
of the transect. Another possibility is that there may be a different type of sand, and subsequent albedo, in this region. Either or both of these could result in the minor change in slope in the shallowest 2 m of the scene.

The output of our technique is analogous to that of Lyzenga, in that both methods generate pseudo-color bands whose numerical values have no readily interpretable physical meaning. A distinction is that output from Lyzenga’s method represents a mixing of two color bands, while output from ours is a set of independently decorrelated color bands. The principal advantage is that our method maintains the relative intensities of different bottom reflectors within the primary wavebands, which provides for more direct knowledge-based interpretation. There is also potential that our pseudo-color bands may be calibrated to absolute reflectance through techniques such as the empirical line method, thus allowing application of spectral classifiers built using libraries of \textit{in situ} reflectance data.

Because it is a rotation of axes into a new coordinate system, this method requires a depth value for each pixel to be rotated. In this study we have a best case scenario: the footprint of the LIDAR data is very close to the pixel size of the multispectral image, and we therefore have accurate values with which to perform the rotation. It may be possible to utilize depth data from a lower resolution source, interpolating to the resolution of the color bands. Provided that the interpolated surface adequately (though “adequate” has yet to be quantified) represents actual depth variations, rotation should provide significant decorrelation.

In summary, we have developed a method to decorrelate color band data from depth in optically shallow water. The method follows ideas introduced by Lyzenga.
(1978; 1981; 1985), but differs in that individual In-transformed color bands are rotated against a bathymetry band rather than other color bands. The method produces pseudo-color bands that are suitable for direct knowledge-based interpretation or for calibration to absolute reflectance. Since this model will work on any single color band that is paired with known depths, its utility is not limited by number or range of color bands, but rather by depth-of-detection within each band. The method is both simple and efficient, and it is potentially useful in remote sensing applications aimed at studying the seafloor.
4.1 INTRODUCTION

Sandy substrate is an important component of littoral and marine habitat, a valuable resource for beach renourishment and construction, and a dynamic aspect of the bathymetry. The shape and form of nearshore sands have a pronounced effect on shoreline stability and constitute a significant portion of the coastal zone geologic framework.

Surprisingly, given the significance of nearshore sands in the coastal environment, relatively little is known of shallow reef-top sand bodies on low-latitude coasts. The goal of this study is to characterize meso-scale (10’s of square meters to square kilometers) spatial patterns of sand occurrence on a subset of fringing reefs on the high volcanic island of Oahu, Hawaii (Figure 4.1). We develop a generalized classification system based on spatial statistics that improves our understanding of the pattern of sand distribution on fringing the reefs.

The sandy substrate of Oahu is primarily carbonate. In contrast to continental locations, where siliclastic sediment is supplied by streams and erosion of coastal sources, the reef-top sands of Oahu are primarily supplied by marine organisms (Harney and Fletcher, 2003; Harney et al., 2000; Moberly et al., 1965). These accumulate in relatively thin patches, fields, and linear deposits that are “perched” on the narrow fringing reefs surrounding the island. Their presence results from a state of semi
equilibrium among various processes controlling the sand budget including biologic production, temporary and permanent storage, and loss (including abrasion, dissolution, bioerosion, and offshore transport). Only two studies, (Moberly et al., 1975; Sea Engineering, 1993) have cataloged these reef-top sands.

Our study focuses on the sandy substrate extending from the shoreline to approximately 20 m of water depth. This depth zone is significant for several reasons. Because of water circulation and nutrient availability, wave climate (Grigg and Epp, 1989; Grigg et al., 2002), and available light, both coral and algal growth rates are highest in these depths (Stoddart, 1969). As most sediment on the reef is produced by reef builders, reef dwellers, and reef bioeroders, this zone is the primary source of nearshore sands. Sand production on Hawaiian reefs is associated with productivity rates of organisms such as foraminifera, mollusks, coralline (red) algae, echinoids, corals, and Halimeda (Moberly et al., 1965). These sand sources are found in two primary locations on the reef platform (Harney et al., 2000). The offshore reef platform is a primary source for framework sediments (coral and coralline algae), while nearshore hardgrounds and landward portions of the reef platform are sources of direct sediment production (Halimeda, mollusks, and foraminifera). Only in the last 8500 years has sea-level rise and shoreline transgression led to the inundation of this portion of the reef (Grigg, 1998) and allowed for modern carbonate accretion (Fletcher and Sherman, 1995; Grigg et al., 2002; Harney and Fletcher, 2003; Harney et al., 2000).

Most waves reach wave base within the zone 0-20 m and convert their energy into shear stress across the sea floor, providing a means for mechanical abrasion of both carbonate framework and direct sediment producers such as Forams and Halimeda
On Oahu, 20 m marks the approximate edge of the nearshore shelf that terminates in a shallow, seaward facing scarp that is part of the Kaneohe Shoreline Complex evident around much of the island (Fletcher and Sherman, 1995; Stearns, 1974). By extension of the Hawaiian eolianite model proposed by Stearns (1970) and modified by Fletcher, et al. (2005) where this scarp prevents sand transport upslope by winds during times of lowered sea level, it may also act as a barrier for shoreward submarine transport except where it is channelized, similar to the fossil barrier reef off southeast Florida (Finkl, 2004).

Importantly, airborne and satellite sensors are capable of accurately imaging the sea floor within this depth range, allowing us to prospect for sands via satellite imagery. Use of remote sensing data is integral to this process as it allows the analyst to begin with a spatially referenced data set, thereby removing the need to create a base map. As such, all results are spatially referenced, and mapped, with each step of the process, creating a Geographic Information System (GIS) by default. Lastly, a standardized method enables analysis of large areas with similar data sets to produce a quantifiable set of results, comparable on measurement and geologic scales.

These results are interpreted to identify patterns in sand distribution according to reef type, geomorphology, geology, and hydrologic environment. Sand deposit types that contribute significantly to reef top surface coverage, environments that facilitate sand storage, and reef types that contain high percentages of surface coverage are identified from these results.
4.1.1 Geologic Framework

4.1.1.1 Insular Shelf

Within the depth range of 0 to 20 m, morphology of the shelf around Oahu results from carbonate accretion during marine transgressions and weathering and erosion during marine regressions as part of recent interglacial cycles. Most of the shelf in this depth zone is reefal in structure and Marine Isotope Stage (MIS) 7 in origin (Sherman et al., 1999). The front of the shelf is characterized by reefal carbonates from MIS 5a-d, and the shallow landward portion in some areas is covered by eolianites of similar age. Covering the shelf in a patchy distribution around the island and filling in available accommodation space are Holocene reef carbonates (Grigg, 1998; Grossman and Fletcher, 2004; Rooney et al., 2004). Circumferential to Oahu, the shelf is almost entirely a fringing reef system, with the exception of Kaneohe Bay and possibly Keehi Lagoon, both of which are classified as lagoons with barrier reefs, or reefs intermediate between barrier and fringing (Guilcher, 1988).

4.1.1.2 Coastal Plain

Coastal plains of various widths fringe sections of the island. Both the Honolulu and Ewa Plains are examples of large insular coastal plains. These are primarily reefal carbonate in structure, dating from MIS 5e (locally known as the Waimanalo Stand) (Muhs and Szabo, 1994; Szabo et al., 1994). Sea level was approximately 1 to 3 m above present during this time, and fringing and barrier reef systems probably developed around the edge of the island. In later stages, when sea level was lower (MIS 5a-d and MIS 2-4), coastal dune systems developed and were lithified on portions of these plains. These
carbonate plains stand at their present elevation (+3 to > +6 m) through a combination of flexural uplift of the island and relatively higher sea-level at the time of their accretion (MIS 5e).

Following the mid-Holocene sea-level highstand ca. 3500 yrs ago (Easton, 1977; Easton and Olson, 1976; Fletcher and Jones, 1996; Grossman and Fletcher, 1998; Stearns, 1977), island shorelines experienced regression and active beach systems prograded seaward, creating beach ridge strand plains along certain sections. Modern shorelines are experiencing widespread transgression, inferred to be the result of eustatic rise and human interruption of littoral processes. The present make-up of the coastal plains, depending on their location, is a combination of modern wetlands, fossil reef (Holocene and MIS 5e), eolianite (Holocene and MIS 5a-d), paleosol (caliche), stranded Holocene beach ridges, mobile sands, and alluvium, with much of the solid carbonate substrate showing signs of karstification from subaerial exposure.

4.1.1.3 Inland Region
Inland from the coastal plains are valley systems that extend landward to the Koolau and Waianae Mountain Ranges. These contain deposits of alluvium in their centers extending out into the coastal plains, and colluvium along the sides of their eroded ridges. These ridges, largely composed of lava and pyroclastic beds, extend across and bisect island coastal plains.
4.1.1.4 Rainfall/Watershed

Much of the annual rainfall on Oahu is controlled by the orographic effect of the mountain ranges on the warm, moist trade winds. Consequently, the eastern (windward) section of the island, along both sides of the Koolau Range, receives much higher annual rainfall than the rest of the island. Kona conditions, or southern winds, increase rainfall along the southern slopes of the island as well as island wide, and hurricanes bring intense rains that are also island wide. The northern section of the Koolau Range receives the highest rainfall (between 3 to 8 m annually), with the southern section receiving slightly less (between 3 and 4 m annually).

Windward peaks on the Waianae range receive a maximum of 2 m annually, with the leeward side of the range receiving less than 0.8 m in some areas. How these conditions differed during past global climatic stages is unknown, although significantly lower sea stands may have intensified the orographic process.

4.1.1.5 Wave Climate

Wave energy impacts accommodation space and mechanical abrasion on the reef, coastline stability, and nearshore submarine sand transport. Bodge and Sullivan (1999) described four main components of Hawaii’s regional wave climate. In the northwest Pacific, high-energy waves are created by winter storms with prolonged high winds directed at the northwestern shores of Hawaii. These waves are incident to shorelines facing from WNW to NNE with typical heights of 1.5 – 4.5 m and periods of 12 – 20 seconds, and extreme heights measured to 15 m. In the south Pacific, high winter (northern hemisphere summer) waves are created between April and October. These south Pacific waves typically have deep-water heights of 0.3 – 1.8 m and periods of 12 –
20 seconds. Infrequent Kona storms produce moderately high-energy waves (around 9% of the year) that approach from the south and west with heights of 3 – 4.5 m and periods of 6 – 10 seconds. Trade wind waves, the most consistent year-round wave type, have moderate energy and approach from the northeast quadrant ~ 75% of the year, for 90% of the summer months and 55 – 65% of the winter months (Grigg, 1998). Trade wind waves have heights of 1.2 – 3 m and periods of 4 – 10 seconds. In addition to these four main types of waves, there are also the infrequent but highly destructive hurricane waves that impact nearshore reefs (Grigg, 1998).

4.2 METHODS/MATERIALS

Analyzing the two-dimensional meso-scale (10’s of square meters to square kilometers) surface characteristics of reef-top sands is a first step in improving understanding of their spatial distribution. Though a spatial analysis fails to incorporate sand thickness, temporal variability, and sediment composition properties, it is nonetheless useful for identifying surface characteristics associated with reef and upland geomorphologies that are helpful for inferring sand deposit origin and history.

Our technique follows a specific series of steps. First we identify study regions within our study area, acquire the remotely sensed data (imagery and bathymetry), and corregister these data. Next we process the corregistered data to remove the effects of light attenuation on the imagery and use several techniques (both analytical and subjective) to discriminate sandy substrate within the imagery. We quantify the accuracy of this step using a confusion matrix for error analysis. We then separate the sandy substrate into individual sand deposits and measure six shape characteristics for each.
These measurements are used to quantify a sand deposit class structure that we implement with a quadratic classifier. We use another confusion matrix to assess accuracies for this step. We then segment these data into three depth controlled sub-environments using measured depths from our bathymetry data. A qualitative segregation of the data is conducted on each sand class, where sub-classes defined by sand deposit shape, reef geomorphology, and hydrologic environment are identified by the analyst. Last, all data are interpreted to identify sand types that contribute significantly to reef top surface coverage, environments that facilitate sand storage, and reef types that contain high percentages of surface coverage are identified from these results.

4.2.1 Study Regions

Study sites are chosen based on quality of available imagery, diversity of the nearshore region, and representation of distinct types of shorelines. These are spread around the perimeter of Oahu, and cover approximately 39% of the total length of shoreline and 125 km² of reef. Nine Oahu study regions are defined using available QuickBird Satellite images (Figure 4.1).

Study regions on the windward side of the island include Lanikai, Kailua, Mokapu Point, Kaneohe, South of Laie Point, and North of Laie Point. These six regions all receive trade wind waves and refracted winter swell. Following is a description of the sites from south to north.

Lanikai region extends from the northern portion of the Waimanalo coastal plain, a beach ridge strand plain, to Alala Point in Kailua Bay. Lanikai region has a broad (>0.5
km) and shallow (2-3 m depth) back reef with a very shallow reef crest (intertidal in places).

Kailua region, a modern beach system fronting a beach ridge strand plain backed by a freshwater wetland, extends from Alala Point in the south to Mokapu Point in the north. Kailua Bay has a relatively deep back reef (3-10 m), a deep reef crest (8-15 m), and is characterized by a large nearshore sand field and prominent sand channel in its center.

Mokapu Peninsula is the division between Kailua and Kaneohe Bays. The seaward shoreline of Mokapu Peninsula receives both direct and refracted winter swell. This broad headland, comprising several post-erosional volcanoes enclosed by coastal plains, has a relatively narrow fringing reef (<0.5 km) with a reef crest near to shore on its seaward coast.

Kaneohe region extends from Mokapu Peninsula in the south to Kualoa Point in the north. Only the barrier reef and the connected fringing reef on the north end, and not the lagoon and patch reefs, are analyzed for this study.

South of Laie Point region is a modern beach system on a narrow coastal plain bounded on the north by Laie Point at the end of Laniloa Peninsula. The peninsula is an eolian headland likely dating from MIS 5a-d. The region extends to Punalu’u Valley on its southern margin, and includes several watersheds that receive the highest annual rainfall on the island. The nearshore is characterized by a generally broad (>0.5 km) and shallow (1-3 m) back reef and a distinct reef crest that is cut by multiple sand channels.

North of Laie Point region, a modern beach system on a broad coastal plain at the feet of gently sloping valley systems, begins at Laniloa Peninsula and extends north to
Kahuku. This region has a narrow and discontinuous back reef containing several eolianite islets, and is exposed to direct and refracted north Pacific swell.

Waianae region is a single large region on the western side of the Waianae Range, receiving direct and refracted north Pacific swell, waves from Kona storms, hurricanes, and south Pacific swell. The coastal plain is a mixture of reefal carbonates from MIS 5e, eolianites from MIS 5a-d, and terrigenous sediments, as well as several modern carbonate beach systems. The region extends from Keaau Valley in the north to Nanakuli Valley in the south. Annual rainfall across this entire region is the lowest on the island. The reef has variable width (<0.5 km - >1 km) with sporadic and narrow back reef sections cut by channels.

The southern side of the island has two regions, Honolulu and Keehi Lagoon. This side of the island is exposed to waves from Kona storms, hurricanes, and south Pacific swell, as well as refracted trade wind waves. Honolulu region extends from the eastern side of Diamond Head to the western side of Honolulu Harbor, an inflection point in shoreline orientation. Honolulu region faces south-south-west and Keehi Lagoon region faces south.

Keehi Lagoon region is bounded on the west by the channel into Pearl Harbor. Much of both Honolulu and Keehi Lagoon regions are artificially filled wetland. These are located on the Honolulu plain, which is underlain by karstified reefal carbonates buried under alluvial outwash. Both regions have also been significantly altered with structures, sand placement, and filled land. They are characterized by narrow fringing reef (<0.5 km) with extensive spur and groove morphology bordering offshore sand fields.
4.2.2 Remotely Sensed Images

Four images were used in this study to characterize sediment distribution patterns in nearshore waters of Oahu. QuickBird Satellite scenes for this purpose were provided by DigitalGlobe, Inc., at http://www.digitalglobe.com. These are georectified, multi-channel (blue 450-520 nm, green 520-600 nm, red 630-690 nm, and NIR 760-900 nm), TIFF images of Oahu, Hawaii, with 2.4 m pixel resolution. Lanikai, Kailua, Mokapu Point, and Kaneohe regions are portions of scene ID 03MAR13205953, acquired on March 13, 2003. Both North and South of Laie Point regions are sections of scene ID 1010010002B85A01 acquired on February 18, 2004. Waianae region is scene ID 101001000173E702 acquired on November 11, 2002. Honolulu and Keehi Lagoon regions are portions of scene ID 1010010002D75F04 acquired on April 7, 2004.

4.2.3 LIDAR Bathymetry

SHOALS (Scanning Hydrographic Operational Airborne Lidar Survey) LIDAR (Light Detection and Ranging) was acquired and processed by the U.S. Army Corps of Engineers (USACE). Data for Kailua region were acquired in 1999 and provided by the U.S. Geologic Survey (USGS). Data for all other regions were acquired in 2000, and provided by the USACE. LIDAR coverage for the island of Oahu is both complete and dense, with an average nearest distance between points of ~2.8 m. LIDAR points for each site (± 5 cm vertical resolution) were interpolated using the Natural Neighbors technique in ArcGIS, and rasterized to a pixel size of 2.4 m. Figure 4.1 (above) is a mosaic of the interpolated bathymetry, shaded for the depth range sea level to 35 m, for all study sites.
4.2.4 Image Processing

Following the method in Conger et al. (In review), we decorrelated both blue and green bands from depth. This procedure utilizes coregistered bathymetry and satellite datasets. They may require a linear shift of 5-20 m for correct alignment. The deepwater component of each band is subtracted, and all subaerial regions, surface disturbances, highly turbid waters, and LIDAR abnormalities are removed. An ln-transform of the band data linearizes the exponential attenuation of light through the water column (Lyzenga, 1978). Sample pixels are selected across the 0 to 20 m depth range from a single substrate type (Mumby et al., 1998). Carbonate sands are used for this because of their easy identification and presence at most depths. These sample pixels are used to model light attenuation with depth. By choosing a single substrate type the variability resulting from different bottom types is minimized. This permits modeling the variability in each band’s intensity values, associated with changing water depth. Principal Component Analysis (PCA) describes the relationship between depth and light attenuation. From this a coordinate transformation is applied to an entire band of data (Rencher, 2002). Output from this data set rotation is a color band that is decorrelated from the effects of the water column, i.e. a bottom reflectance image where individual substrates no longer become darker as the water column becomes deeper. Figure 4.2A shows the rotated blue color band for a section of Kailua Bay reef. This area was chosen to utilize data and results from Isoun et al. (2003) for water quality and reef cover.
4.2.5 Substrate Discrimination

Several techniques are used to identify marine sand in the images. Techniques include classification algorithms, band density slices, and analyst selection. The final combination of techniques is both analytical (classification algorithms and band density slices) and subjective (analyst selection based on ground truth data). Variation in water column properties, atmospheric properties, and sea surface state over large regions necessitated the use of several techniques for each area.

Simple classifier algorithms, e.g. minimum distance and Mahalanobis distance (Richards and Jai, 1999), are used to discriminate substrates into two categories, “sand” and “not sand.” Figure 4.2B shows the classified image for a section of Kailua Bay reef. For large areas or heterogeneous water bodies, application of a band threshold tool is also used. This tool allows the analyst to identify a specific intensity level within a single color band. Carbonate sands (which tend to be very bright) may be distinguished from other substrate types (darker) in this way. An advantage to this method is that by adjusting the specific intensity level, or threshold, for the “sand”/“not sand” boundary, it is possible to accommodate variable water quality characteristics that otherwise introduce error (e.g. suspended sediment will either lighten or darken an area depending on the material). Last, some sections of each scene are defined by the analyst using hand digitization. These locations, while readily identifiable by an analyst, are not entirely identified by the other techniques. This is typically necessary adjacent to steep slopes and where the imagery or LIDAR data are not usable. In these locations sandy substrate is
identified on the basis of field observations. The final result is a sand identification image of the entire study area, as seen in Figure 4.3.

Accuracy for substrate discrimination is assessed by two methods: analyst interpretation and test statistics. We focus on analyst interpretation at intermediate steps, which permits choosing the best combination of discrimination techniques based on spatial accuracy. After the process is complete for a region, then we use test statistics, as computed in a confusion matrix to assess our accuracies for discrimination. Only after we are satisfied that identified sand deposits are spatially well represented, and we have sufficiently high classification accuracies (~95%) do we accept our substrate discrimination results.

4.2.6 Shape Analysis

Once the sand deposits are identified, the image is segmented, using ENVI software, so that individual sand deposits have their own identification number. We identify a total of 14,037 sand deposits. We use Matlab to calculate a set of shape measurements for each sand deposit. We use six measurements, they are: area, orientation, eccentricity, form factor, roundness, and solidity. Table 4.1 lists these measurements, their formulas, and a short description of their physical meaning.

4.2.7 Sand Deposit Classification

In order to identify discrete classes of sand deposits we use a supervised classification algorithm that employs five training classes defined by the analyst. These classes are described in Table 4.2. They are: 1. channels and connected fields, 2. complex
fields and very large depressions, 3. large depressions and fields, 4. linear deposits, and
5. small depressions and simple fields.

This class structure was chosen, after substrate discrimination, by selecting the
most common deposit shapes associated with important reef geomorphologies. Several
iterations of class and shape selection were necessary to produce a final class structure
that has both physically meaningful (geology and geomorphology) and analytically
meaningful (appropriate, accurate, and repeatable sectioning of shape measurement data)
results. Final sand deposit training classes contained a small number of deposits for each
class (<= 25). A quadratic classification algorithm, in Matlab r13, using shape
measurement data for all sand deposits, separated them into our five-class structure.

Accuracies for this sand deposit class structure were assessed using a confusion
matrix for the training class data. We chose to accept a class structure when most
accuracies were above 80%.

4.2.8 Sub-Environments

The five sand deposit classes are split into three depth groups representing
hydrologically controlled sub-environments. Since our study regions are exposed to
variable hydrologic climates, we chose to recognize three basic depth groups: 0-10 m, 10-
20 m, and crossing the 10 m contour. This grouping provides insight to sand storage
variability controlled by depth. The 10 m contour approximates the boundary of two
important reef sub-environments: 1) shallow reef limited by wave-generated shear forces
where bathymetry largely reflects antecedent karst morphology, and 2) deeper reef where
wave forces are less significant and the bathymetry is more likely to reflect modern reef
accretion. The 10 m contour is characterized by intermediate, or transitional depths where the substrate is some combination of karst morphology modified by modern reef accretion. Comparing these depth groups highlights the ability of the reef to store sands. It also provides insight into sediment transport patterns as shear stress from wave-generated and tidal currents determines sediment transport (Cacchione and Tate, 1998; Storlazzi et al., 2004) across the reef surface, and is controlled largely by water depth.

This is an analytical process that assigns all sand deposits to a sub-environment by their range of depths, using bathymetry interpolated from LIDAR data. Sand deposits that are identified as 0-10 m and 10-20 m sub-environments are removed from both and placed into the sub-environment crossing 10 m. This sub-environment is likely effected by the size of sand deposits within a class, e.g. classes with large deposits are likely to have higher percentages in this sub-environment than classes with small deposits. This sub-environment also varies from the other two, in that it only identifies sand deposits that cross this specific depth, while the others identify sand deposits that occur across a range of depths. However, this sub-environment structure provides significant data for understanding sand distribution patterns as they relate to the hydrologic environment.

4.2.9 Sub-Classes

After all analytical segmentation of the data is complete (individual sand deposits, sand deposit classes, sub-environments) a final step of qualitative sub-classification is performed. This requires the analyst to interpret individual sand deposit classes to identify groups that occur in specific environments. This step does not utilize shape measurement data, but rather the analyst’s interpretation of where portions of each sand
deposit class occur on the reef. Consequently, it is not possible to give specific measurement ranges, create a supervised classification structure, or analyze accuracies via a confusion matrix.

4.3 RESULTS

The study area comprises nine regions, totaling approximately 125 km² of reef. Total surface area of identified sand deposits is about 25 km² or ~20% of the total reef area. Accuracy assessment for sandy substrate identification is detailed in a confusion matrix for substrate test pixels (Table 4.3). A confusion matrix has two important outputs, the producer’s accuracy and the user’s accuracy. Producer’s accuracy describes error of omission (how accurately are known class members properly identified). User’s accuracy describes error of commission (how often an identified class contains known members). All accuracies were better than 95% for substrate discrimination.

*Channels and connected fields* account for the majority (64%) of all sand deposit surface area, and *complex fields and very large depressions* account for 18%. Just over 72% of all sand deposit surface area straddles the 10 m contour line, and 24% is shallower than the 10 m contour line. Combined sands crossing or shallower than 10 m represent more than 96% of all sand deposit surface area. When deposit classes are distinguished by depth range, *channels and connected fields* that straddle the 10 m contour account for 63%, *complex fields and very large depressions* shallower than 10 m account for 10%, and *complex fields and very large depressions* that cross the 10 m contour account for 7%. Together, these three subgroups total 80% of all surface area for sand deposits.
Study region boundaries are determined by physical variation of coastline and reef, not size constraints. Hence we analyze sand deposit surface coverage as a normalized percent of reef cover as well as by total surface coverage. Figure 4.4 illustrates differences between total surface coverage and percent regional reef coverage. Regions containing the greatest absolute sand cover are Kaneohe and South of Laie Point (Figure 4.4A). However, normalized sand cover is greatest in Honolulu and Keehi Lagoon regions (Figure 4.4B).

Figure 4.5 displays a glyph plot for each region. Glyph plots are star shaped plots that assign spokes to each of five shape measurements for each region. The shape measure called orientation, is not included because in an island setting shorelines are oriented to all points on a compass. Longer spokes indicate a higher value relative to the other regions. An example glyph is provided, with the measurements represented by each spoke labeled. Normalized percent total reef coverage is used for area. Each glyph displays mean values for eccentricity, roundness, form factor, and solidity for each region. Two areas of the glyph are shaded in the example to illustrate one way to interpret these plots. Complexity indicates a high degree of variability in the shape of the sand deposit. Elongation and circularity indicate generalized geometries of sand deposits.

Ultimately we wish to understand where the sand is. Dividing the sand deposits into classes is an informational tool allowing us to define patterns within the data and map out variation between regions. Quantifying the validity of our five classes is possible by computing a user’s accuracy from a confusion matrix (Table 4.4). Accuracies are above 90% for all classes except channels and connected fields. This class has a lower
user's accuracy because it identifies some deposits from other classes as its own, but this does not significantly change the accuracy of the classified total sand surface area.

To improve our understanding of the origin and significance of each deposit class, it is helpful to look at their average shape measurement. Table 4.5 lists the shape measurement means and standard deviations for each deposit class. Included in the table are bitmap images of examples for each class, which are helpful for understanding actual sand deposits that are associated with specific shape measurement statistics. Glyphs for each class, created from the values listed, and short descriptions, are included to clarify relative variations in measurement. Also included are small images of sand deposits in each of 14 subclasses. These subclasses are identified by geologic analysis from each of the classes identified by our supervised classification algorithm.

Analyzing sand deposit class distribution for the entire study area and among individual study regions is an important step in improving our understanding of environmental factors contributing to sand storage. Figure 4.6 contains bar plots of percent sand coverage for each class. The sum of all sand deposit classes is depicted in the “All Regions” plot showing the sand distribution pattern for the entire island-wide study area with the following values: *channels and connected fields* (64%), *complex fields and very large depressions* (18%), *large depressions and fields* (10%), *linear deposits* (2%), and *small depressions and simple fields* (6%). The Honolulu region class distribution pattern is the closest to that of the entire study area, while several regions (i.e. Lanikai, Mokapu Point, and North of Laie Point) have significantly different class distributions.
4.4 DISCUSSION

The focus of this research is to identify sand deposit types that contribute significantly to reef top surface coverage, environments that facilitate sand storage, and reef types that contain high percentages of surface coverage. Our technique follows a specific series of steps to achieve these goals. Identifying study regions, acquiring remote sensing data, and removing the effects of light attenuation on the imagery are preprocessing steps that do not require discussion. However, the use of several techniques (both analytical and subjective) to discriminate sandy substrate within the imagery and use of a quadratic classifier for sand deposit classification both require error analysis before their results should be accepted for further analysis. Between these two data segmentation steps we identify individual sand deposits and measure six shape characteristics for each. These steps are purely analytical and require no discussion. Similarly, segmentation of sand deposits into depth controlled sub-environments from bathymetry data does not require either error assessment or discussion. The qualitative sub-class structure as defined by sand deposit shape, reef geomorphology, and hydrologic environment are identified by the analyst. For this step there is no error assessment, as no measurements or physical values are associated with these classes.

4.4.1 Error Analysis

Several caveats to image processing and classification should be mentioned. First, normal image processing assumes both vertical and horizontal homogeneity within the water column. As this is not usually the case, we process the images in several sections reflecting different water quality areas. Second, light attenuation in the water column
confuses attempts to discriminate substrates as intensities change with depth. To solve this problem, we decorrelate a color bands from depth, a process that requires two initial values for each pixel (intensity and depth). However, if either intensity or depth are incorrect, this processing step will be incorrect as well. This is often the case where LIDAR data are not present or are incorrect, or the imagery is obscured by clouds or sea-surface clutter. We mask out these regions to remove them from processing and further analysis. Third, this process requires optically shallow waters, meaning that water must be sufficiently clear and shallow for the sensor to record an image of the bottom. This is why we do not use the red and near infrared bands, as they provide very little water penetration. Fourth, distinction between "sand" and "not sand" can be subjective; the definition of these two categories comes from a continuum of substrate variation (as sand grades into hard substrate, rubble, algal meadows, etc.) and is an analyst decision.

Substrate discrimination techniques, both analytical and subjective, are used to facilitate this distinction using both measured data and its placement on the reef. Quantifying this steps accuracy is central to this technique. We found our accuracies, all above 95%, to be sufficient high to assume substrates identified as "sand" are actually sand. Fifth, selection of training classes is a process of choosing sand deposit shapes, by their placement on the reef, that are separable into distinct classes, by their shape measurement data. This was an iterative process that we found to be acceptable when most class accuracies were above 80%. At this point we assumed that sand deposits identified as a certain class would repeatedly be chosen as that class and are indicative of the physical definitions we attached to that class. *Channels and connected fields* class error was lower then 80%. The misclassified shapes in this class account for only a small portion (<1%) of the overall
sand deposit surface coverage though they have a significant effect on calculated user’s accuracy for the classification algorithm. Since understanding where sand is stored is the goal of this study, minor effects on total sand storage are considered negligible, even though user’s accuracy is lower.

4.4.2 Deposit Classes

Total population statistics for 14,037 sand bodies identified are indicative of both Oahu’s sand distribution patterns and, to some degree, its reef geomorphology. The total population is segregated into five sand deposit classes each containing numerous individual sand deposits: *channels and connected fields* (97), *complex fields and very large depressions* (103), *large depressions and fields* (1282), *linear deposits* (1618), and *small depressions and simple fields* (10,937). Each of these is a continuous sand body on the reef surface; most are located in local depressions within the regional bathymetry. These bathymetric lows are the product of both sub-aerial exposure of the fossil reef and modern reef accretion. The degree of influence these two processes exert on reef morphology is largely controlled by depth of water (including past sea-level lowerings) and wave climate; thus discussion of our depth groups is vital to understanding each sand deposit class.

The five sand deposit classes are each defined by unique assemblages of quantifiable shape measurements, as seen in Table 4.5. However, within each of these there are identifiable subclasses that we qualitatively define through analyst interpretation. Our final sand deposit class structure is as follows:
1. *channels and connected fields*
   a. “major channels”
   b. “transitional channels”
   c. “sand-starved channels”
   d. “unchannelized drainage”
   e. “misclassified deposits”

2. *complex fields and very large depressions*
   a. “fields with steep boundaries”
   b. “reefal strandlines”
   c. “radial lineations”
   d. “very large depressions”
   e. “open fields”

3. *large depressions and fields*
   a. “large depressions”
   b. “fields”

4. *linear deposits*

5. *small depressions and simple fields*
   a. “small depressions”
   b. “simple fields”

4.4.2.1 *Channels and Connected Fields*

This deposit class accounts for more than 64% of total sand surface area while comprising less than 1% of individual sand deposits. High mean eccentricity (0.945) and
low mean roundness (0.128) combined with low mean values for both form factor (0.091) and solidity (0.422) depict elongate, narrow, moderately winding shapes with complex borders. From shape measurements alone, the glyph is almost opposite that of small depressions and simple fields. When considering the physical parameters of channels and connected fields, as large sediment conduits across the reef surface, they contrast obviously with small, isolated deposits. Figure 4.7 shows all deposits in channels and connected fields within the study area.

The first sub-class, “Major channels” is easily identified through either bathymetry or an image of the reef and are accurately identified by our sand deposit classification. When filled with sand, these units almost always connect to both nearshore and offshore sand fields and act as conduits for sand movement in both onshore and offshore directions (Cacchione and Tate, 1998). The example in Table 4.5 is indicative of a “major channel” in our study area, where the main channel is connected to two sand fields (offshore and nearshore). Imagery of the offshore sand field in this case terminates at the lower limit of light attenuation, not at the physical extent of the sand field.

“Major channels” are likely the result of superimposed streams that incised fossil reef during sea-level low-stands. In every case, channel axes are aligned with their respective modern drainage systems in the adjoining watershed, except where human influence has shifted outlets. During sea-level low-stands, Oahu’s current reef area was sub-aerially exposed and streams connected the drainage system to the ocean across the exposed carbonate shelf. Sand deposits in these features are typically shore-normal in orientation, except where several stream channels feed into one sand deposit that is usually an offshore sand field (i.e. Waianae, Honolulu, and Keehi Lagoon regions). All of
the sand deposits in this class cross the 10 m contour, and when combined with those in the subclass “unchannelized drainage” (also in the sub-environment crossing 10 m), they account for almost 63% of the total sand coverage, and almost all the *channels and connected fields* sand coverage.

The two subclasses “transitional channels” and “sand-starved channels” both lack connectivity between nearshore and offshore sand fields. That there are few examples of these two subclasses on the reef reflects the fact that it is very rare for a channel across a reef to be filled with debris and modern growth (Purdy, 1974). This is certainly the case for all the “major channels” developed from broad superimposed paleo-streams. Grossman and Fletcher (2004) drilled the walls of the paleo-channel in Kailua Bay and found that though reef accretion is extensive on the walls, it was not nearly sufficient to close the channel. However, immediately to the south is the Kaelepulu channel, a much narrower “transitional channel” being closed by modern accretion. In 10-20 m depth, where accretion generally dominates modern morphology, this channel is expressed as a series of separated depressions classified as *linear deposits and large depressions and fields*. Though these depressions hold distinct sand deposits, they are all still connected by a winding and narrow depression in the reef (Kaelepulu paleo-channel). Notably, in the 0-10 m depth, where antecedent topography controls bathymetry, the channel is properly classified as a sand channel.

This location emphasizes two issues. First, our classification system works where channels maintain original morphology. Second, sand deposit morphology in the depth range 10-20 m is controlled by the reef’s ability to grow into accommodation space more than by the conduit’s ability to transport sand. Also important is the close proximity of
this “transitional channel” to a “major channel”, both of which share common hydrologic and ecologic environments. This implies that a combination of channel width and depth are needed to preserve both channel morphology and sand conduit capability.

A completely broken channel, no longer an active conduit of sands, is a “sand-starved channel.” Several examples of “sand-starved channels” can be identified in the bathymetry. The difference, when compared to a “transitional channel,” is that “sand-starved channels” are blocked by lithified outcrops rather than debris and modern accretion. One example is a former channel that has been bisected by Laniloa Peninsula, an eolianite outcrop dating from MIS 5a-d (Fletcher et al., 2005). The outcrop bisects the channel and is therefore younger. The eolianite was deposited and lithified during lowered sea-levels at the end of the last interglacial when that section of the reef was sub-aerially exposed. These “sand-starved channels” contain only limited patches of sand, but they provide interesting examples of sand storage response when nearshore and offshore sand deposits are not connected. Though active channels may have outcroppings of rock within channel walls, the distinction of “sand-starved channels” is that some rocky outcrops extend across the width of the channel and are higher than channel walls.

“Unchannelized drainage” is correctly classified by our algorithm as channels and connected fields. Analyzing local watershed and drainage patterns shows evidence of small waterways related to flood drainage or wetlands during lower sea-levels. These are minor drainage systems that were never sufficiently active to cut permanent channels through the sub-aerial, porous limestone. The result is a group of interconnected, sand-filled depressions extending from the shoreline down to the offshore fields. This type of drainage is likely the product of karst processes acting on the carbonate bedrock of the
coastal plain. The best example is the connected and intermingling sand fields off Kuhio Beach in Honolulu region, which is our example shape for the subclass (Table 4.5). Individual “unchannelized drainage” deposits have high surface areas and are in the sub-environment crossing 10 m alongside “major channels”.

The last group of channel types is “misclassified deposits”. These are categorized as a type of channel and connected fields because they have large surface areas, complex shapes, and are elongate in nature. However, these sand deposits do not fit the geologic definition for sand channels and connected fields, and should be considered an error class. Among the deposits included in this subclassification are almost all the known engineered (dredged) depressions. Originally, engineered depressions were identified as large depressions and fields for training the classifier, though their actual shapes are much closer to channels.

The significance of connectivity between nearshore and offshore sands, and the high surface area of these deposits is notable. The conduit nature of this class links areas of sand production with areas of long-term sand storage. Both Moberly et al. and Harney et al. agree that sediments produced on the reef platform fill spaces there, move to shallower nearshore deposits, or move off the fore reef into deeper waters. Harney et al. found sediment production on the nearshore reef feeds sand deposits in the nearshore (including beaches) but eventually moves downslope toward offshore fields that are likely to be terminal depositional sites. These researchers, including Cacchione and Tate (1998), indicate that sediments move both onshore and offshore within “major channels,” and are indicative of a highly connected sand conduit system between nearshore deposits and offshore fields.
“Sand-starved channels,” broken by lithified deposits, are a startling contrast to the well-articulated sediment transport and storage systems of “major channels.” Those channels no longer linking the nearshore and offshore deposits have significantly reduced sand storage within channels walls and among nearshore deposits. These patterns underscore the need for not just sediment production but also shallow-deep connectivity for a fully developed sand deposit system.

4.4.2.2 Complex Fields and Very Large Depressions

*Complex fields and very large depressions* sand deposit class accounts for 18% of the total sand surface area. This does not, however, account for all surface sands that are stored in complex fields, as a large portion of nearshore and offshore sand fields are directly attached to sand channels and classified as *channels and connected fields*. Moderate mean eccentricity (0.851) and roundness (0.269) describe shapes that are neither round or elongate. Very low mean form factor (0.052) and below average mean solidity (0.422) implies a highly complex boundary to the shape. The glyph plot for *complex fields and very large depressions* is noticeably more elongate and complex than other classes *large depressions and fields*, a result of larger fields and more linked depressions creating complex individual sand deposits. Orientations for this class are bimodal with peaks that are both shore-normal and shore-parallel.

The first sub-class is “fields with steep boundaries” are generally offshore sand fields whose shoreward limits are either scarps on the reef face or steep sided morphologies like spur and groove. The shoreward extent of these offshore sand fields is influenced by sediment supply and hydrologic environment. Low energy and sediment
rich areas (our example [Table 4.5] is the Honolulu region) allow offshore fields to extend farther inland than contrasting areas (higher energy and sediment poor), for example in the Kailua region. In the Honolulu region offshore "fields with steep boundaries" extend into spur and groove morphology on the nearshore reef. Deeper spurs help to separate these sand fields from channels, so they are identified as individual deposits that are distinct from channels, though they are likely connected in depths beyond our limit of detection. Lower annual wave energy (neither north Pacific swell nor trade wind waves) allows for greater abundance of sub-environments > 10 m depth, with extensive spur and groove development extending across the reef top. Combined with the occasionally present shallow terrace this provides increased storage space for sands. Interestingly, in our example site (Honolulu) there is little net accumulation of modern reef accretion, as hurricanes seem to destroy most modern framework builders (Grigg, 1995).

"Reefal strandlines" (Blanchon and Jones, 1995) on the back reef are another significant subclass of complex fields and very large deposits. These linear features parallel the direction of wave approach or line up with currents originating from the reef surface. "Reefal strandlines" often extend straight back from the reef crest to near the shoreline, except near the landward portion of channels. At these locations the "reefal strandlines" tend to curve toward the shoreward end of the channel, indicating that nearshore currents strong enough to transport sediments are being focused into the channels and shaping "reefal strandline" deposits. Thus sediment production and storage, following the "reefal strandlines," is linked to both the beach system by wave transport, and the offshore fields by the conduit behavior of the channels. Many of these sand
deposits are connected to the landward ends of channels, and are classified as channels and connected fields. Though these features may cover large surface areas, our research in the Waikiki area suggests that their thicknesses are usually minimal, indicating smaller volumes for such large areal coverage. Individual “reefal strandlines” are generally interconnected on the back reef, producing orientations for groups of “reefal strandlines” that are shore-parallel rather than the shore-normal direction that individual deposits establish.

“Radial lineations” (Guilcher, 1988) are oriented to wave approach across the reef surface. This subclass, similar to “reefal strandlines,” is shaped by wave and current energy as sediment is transported toward the landward margin of the fringing or barrier reef. Though the “radial lineations” are not typically thick deposits, they may adjoin sand cays and other types of sand accumulations on the landward margin of fringing and barrier reefs. Three examples of “radial lineations” and associated sand deposits exist in the study area, two in Keehi Lagoon region and one in Kaneohe region.

“Very large depressions” are likely the result of karst features such as dolines or uvalas developed during subaerial exposure of Oahu reefal carbonates. These features were possibly connected when subaerially exposed, because the reef environment 0-10 m depth tends to preserve inherited karst morphology. However, since these are complex features in shallow water with long-axes oriented in the direction of wave and current approach, it is most likely that these depressions became linked after marine inundation.

The difference in geologic history between “very large depressions” and “fields with steep boundaries” is one of morphologic control due to antecedent topography rather than reef accretion. Very different histories and environments do not, however, affect
potential sand storage space as both create relatively deep and interconnected storage spaces for nearshore sands. “Very large depressions” occur in several noteworthy locations (i.e. Kailua, Keiki Lagoon, and Honolulu regions) as collections of connected depressions.

“Open fields” are found throughout our regions and depth sub-environments. These sand fields appear to be located within shallow depressions in the reef, and often contain many outcrops and irregular perimeters. The outward boundaries of these features are not marked by a steep slope, as are those of both “fields with steep boundaries” and “very large depressions.” Instead, this subclass fills in gentle bathymetric lows, or swales, and tapers out as the basin floor rises to the surrounding hard bottom. Because of the shallow nature of these depressions, many outcrops extend through the sand deposit, and the borders are often very complex. This subclass, though smaller in individual deposit area than the other subclasses, is included in complex fields and very large depressions because of very high complexity values.

4.4.2.3 Large Depressions and Fields

This class is similar to the “very large depressions” and “open fields” subclasses in complex fields and very large depressions. Several key differences exist that distinguish this class from others. Most obvious is reef coverage, or deposit size. Large depressions and fields contribute 10% of the total sand surface area. Overall deposit size accounts for some, but not all, of the lower complexity for this class. Also critical to these lower values are many more single “large depressions” rather than collections of interconnected depressions, and the “fields” fill smaller and less complicated lows in the
bathymetry. As such, many of these features are more rounded or elliptical as well as less complex than complex fields and very large depressions, they tend to generate higher solidity (0.549) and roundness (0.303) values, with lower form factor (0.259) and eccentricity (0.785) values. This class (10% of total surface coverage) is predominately located in 0-10 m depth (7% of total surface coverage).

Of the sub-classes, “fields” is less common, and account for far less total sand coverage than “large depressions.” “Fields” are very similar to “open fields” except that individual sand deposits have less total surface area and are less complex.

Many “large depressions” are single (or only a few connected) karst derived dolines. When located in the vicinity of the reef crest, sand deposits in this class become more elongate and oriented in the direction of wave approach. Dolines, as they are developed in subaerial porous limestone, show preferred orientations parallel to major trends (Ritter et al., 2002). Analyzing preferred orientation in our three depth controlled sub-environments allows us to differentiate the controls on shape and orientation. Sub-environments in 0-10 m depth and crossing the 10 m contour both show preferred orientation in a generally shore normal direction, while sub-environments in 10-20 m depth show no preferred orientation. Though the “large depressions” were created by the same process of subaerial karstification, wave and tidal current energies are needed to preserve and possibly accentuate original depression shapes.

4.4.2.4 Linear Deposits

Linear deposits as a class account for a very small percentage (under 2 %) of the overall sand surface area. These sand deposits fill in linear depressions shaped by
hydrologic conditions, or they are deposited in linear form as a result of hydrologic conditions. Almost all sand deposits in the *linear deposit* class are oriented in the direction of wave and current approach, indicating their strong dependence on wave and current energies. Exceptions occur in two locations: sand deposits located along the shoreline, and large offshore sand deposits that are cropped short by limits of detection within the imagery. *Linear deposits* are located throughout the study area, but over 75% are in 0-10 m depth, again indicating strong control by wave and current energy. These controls are also evident in the shape measurements for this class, as they are very elongate, simple sand deposits. This class has eccentricity values (mean of 0.975) almost equal to a line (1.00); and mean roundness (0.148), mean form factor (0.381), and mean solidity (0.686) values that indicate simple, continuous features with smooth borders.

Most study regions contain similar percent coverage by this class, though Keehi Lagoon and Mokapu Point regions have exceptionally high and low percent coverage respectively. Keehi Lagoon’s back reef (0-10 m depth) and high spur and groove coverage (10-20 m depth) and extensive offshore and midreef sand fields might explain why so many of these individual sand deposits are not interconnected into larger fields. That is, high regional sand supply and limited wave energy allow for more filling of narrow and elongate reef morphology features. In higher energy systems, these depressions would either not be present, or they would not hold sands. The reason for Mokapu Point’s low coverage (0.28 %) is probably related to the lack of a back reef and its higher wave energy environment.

4.4.2.5 *Small Depressions and Simple Fields*
Small depressions and simple fields account for the majority of individual sand deposits, with almost 78% of those identified in this study. However, because of their small size they only contribute 6% of the total sand surface area. Shape measurements for this class are similar to large depressions and fields, though they reflect the simpler (mean form factor of 1.017), rounder (mean roundness of 0.417 and mean eccentricity of 0.821), and more solid (mean solidity of 0.834) characteristics of these smaller and more cleanly outlined deposits. Morphologic features on the reef surface that hold this sand deposit class are very similar to those holding “large depressions,” where most of these deposits are in either karst doline features (“small depressions”) or “simple fields.”

These features are ubiquitous across the depth controlled sub-environments, though most (68% of sand deposits and 75% of surface coverage for this class) are in the sub-environment <10 m depth. Only 2% of these deposits are in the sub-environment crossing 10 m. As the average area for this class is 138 m², these roughly circular deposits would have radii averaging ~5 m. Thus they are very localized and unlikely to fall on a single contour line. Interestingly, this class is slightly more elongate than the larger depressions. Those sand deposits in the sub-environment crossing 10 m have a much stronger shore-normal preferred orientation than the other two sub-environments. More elongate deposits with preferred orientations might result from a combination of several processes. First, doline features are being closed in the deeper sub-environment, where reef accretion controls bathymetry but still has weak orientation control from hydrologic conditions. Second, “simple fields” in the shallower sub-environments tend to include many individual “reefal strandlines,” “radial lineations,” and bending or connected “linear deposits.” Third, those within the sub-environment crossing 10 m give
us a focused image of small sand deposit response across the reef at 10 m. Strong preferred orientation at this depth indicates control by hydrologic conditions forcing a preferred orientation on the reef, and at the same time not allowing reef accretion to completely fill in depressions inherited from the antecedent karst topography.

A portion of this class is the result of pixel resolution being too coarse to image or identify thin connections. The result is that small appendages or extensions that are actually parts of a larger sand deposit are separated as individual deposits. A last note on this class, even though they are called small, the minimum size in this class is five pixels, or 28.8 m², and the average size is 138 m², so they are definitely large enough to be considered in environmental, ecologic, geologic, or resource studies.

4.4.3 Regions

Nine study regions cover three of the four sides of Oahu, Hawaii. Two regions, Honolulu and Keehi Lagoon, are located on the southern, and lowest average energy, shoreline. The six regions on the eastern shoreline can be broken into two basic energy groups, those exposed to more and those exposed to less north Pacific swell. Both Mokapu Point and North of Laie Point regions are exposed to more energy, while Lanikai, Kailua, Kaneohe, and South of Laie Point are exposed to less energy. This entire shoreline is exposed to moderate to high-energy trade wind waves. One region, Waianae on the western shoreline, is exposed to conditions similar to the southern shoreline while also receiving direct and refracted north Pacific swell. No regions were studied on the northern shoreline because of an absence of available data fitting our basic requirements.
4.4.3.1 Southern Shoreline

Of all the study regions on Oahu, the Honolulu region has the highest percent of sand coverage at over 32%. Keehi Lagoon region west of Honolulu, has the second highest percent coverage at 28%. These two regions, covering approximate 13% of Oahu's coastline, are both south-facing beaches on the Honolulu Coastal Plain. The area is partially protected from trade wind waves, shadowed from winter swell, and receives wave energy primarily from Kona storm events, seasonal south Pacific swell, and occasional hurricanes. Typically this is a low-energy environment in front of a wide coastal plain, with a wide back reef and reef crest at variable depth.

Higher sand deposit surface coverage may be the result of several factors. First, following the estimates of Kapapa High Stand productivity by Harney et al. (2000), this shoreline may have experienced increased sediment production, across the wide coastal plains which may have been partially flooded, associated with higher sea levels. Second, though the last hurricane was more than a decade ago, damage to the southern shoreline's reefs from the 1982 and 1992 hurricanes was extensive, leaving piles of cobble and rubble where much of the living reef had formerly been (Grigg, 1995). Third, the area is heavily dredged for channel creation and maintenance, with much of the dredge spoil dumped on the reef surface. Fourth, high non-point source nutrient loading might also lead to increased production and consequent sediment volume increase in the area. These three factors might help to explain the abundance of carbonate sand along the southern shoreline.

This does not explain the disparity in surficial coverage between Honolulu and Keehi Lagoon. These two regions also show distinct differences in sand deposit class...
distribution and overall sand deposit shape measurements, as seen in the glyph plots. Several possible factors might contribute to this disparity. First, Waikiki shoreline in Honolulu region has received multiple sand nourishments throughout the 20th and into the 21st century, of which ~75,000 m³ is no longer accountable on the beaches (Miller and Fletcher, 2003). Assuming this volume has moved onto the nearshore reef, it is enough to cover all Honolulu region’s sand deposits with ~2.5 cm of sand. Second, tidal flood currents accelerate around Diamond Head as they travel westward, increasing the volume of suspended sediment that is later deposited on sand fields <10 m depth in Honolulu region. Third, the reef surface area lost to artificially filled coastline present in the two regions. Honolulu region has multiple, small-area sections of artificially filled coastline. However, the massive reef loss, especially back reef that is a high sand coverage area, resulting from the development of Honolulu Airport’s runways and Sand Island has dramatically reduced reef surface area in the Keehi Lagoon region. It is reasonable to suggest that a combination of these three reasons explains much of the disparity between percent sand coverage in Honolulu and Keehi Lagoon regions, where the general conditions and hydrologic climate are otherwise very similar.

Mean sand deposit shape measurements, as seen in the regional glyphs, show that mean values for Honolulu are distinct from all other regions, and its distribution of surface coverage by classes is almost the same as the entire study area’s population. Keehi Lagoon on the other hand has a sand deposit class distribution similar to Kaneohe region, the other lagoon environment, with high coverage in complex fields and very large depressions and linear deposit classes and lower than average coverage in channels and connected fields class. Keehi Lagoon region is similar to Lanikai in mean sand
deposit shape measurements, as seen by their average glyphs. Though these regions are in
different energy environments, all originally had broad and shallow back reefs connected
to well defined and shallow reef crests. The back in Ke'ehi Lagoon region is limited in
modern extent from artificially extended coastlines discussed earlier.

The southern shoreline, with a wide coastal plain, low-energy environment, wide
and shallow back reef, shallow reef crest, and extensive offshore sand fields is the model
for high sand surface coverage on Oahu. Reefs on the eastern shoreline, Lanikai and
South of Laie Point regions, with similar reef morphologies but higher energy
environments, are the next closest for sand surface coverage. We call this general
morphology and environmental condition “low-energy wide reef” (Table 4.6).

4.4.3.2 Eastern Shoreline

The entire eastern region receives persistent trade wind waves and direct and
refracted north Pacific swell. Trade wind wave energy may be the controlling factor in
the depth of offshore (reef-front) sand fields. These deep fields are scarce within our
remote sensing detection limit along the entire eastern coastline, regardless of exposure to
north Pacific swell. However, offshore sand fields are prevalent on all other sides of the
island, including the western coastline that receives both direct and refracting north
Pacific swell.

The eastern shoreline can be broken into two basic groups, those receiving less
north Pacific wave energy, and those receiving more. Those receiving less north Pacific
wave energy can be further separated by general reef shape and percent sand coverage
(Lanikai and South of Laie Point; Kailua and Kaneohe).
Lanikai and South of Laie Point regions have total percent sand coverage that are similar. They both have wide, shallow back reefs and very shallow and distinct reef crests. Mean sand deposit shape measurements, as seen in the regional glyphs, indicate that deposits in the Lanikai region are closer in shape to the deposits found at Keehi Lagoon.

Kailua and Kaneohe have almost identical total percent sand coverage and mean sand deposit shape measurements (glyphs). Both have prominent headlands to north and south, both have almost the same preferred deposit orientation, similar moderate energy environments, large and active watersheds, very limited sand storage in 10-20 m depth zone, and their offshore sand fields are deeper than our detection limit.

However, these two regions have very different reef geomorphologies. Kailua is a deep fringing reef showing evidence of widespread karstification, dominated by a single sand channel and its connected nearshore sand field. Kaneohe is a barrier reef, with a broad and shallow back reef, and a reef front covered in linear morphologic features on several scales. It has an active sand channel at each end, and multiple large back reef sand fields along the landward margin. These differences are highlighted by sand deposit class distributions. Kailua region shows similarity to the Waianae region, also a deep fringing reef with a narrow and deep back reef, and a reef surface dominated by sand channels. Kaneohe region shows similarity to Keehi Lagoon region, also a reef intermediate between fringing and barrier.

The high-energy environments, Mokapu Point and North of Laie Point regions, are both in front of wide coastal plains, have deep fringing reefs, little to no back reef, and minor identified offshore sand fields. Both these regions have low total percent sand
coverage, similar mean sand deposit shape measurements (glyphs), and similar variations from the average for their sand deposit class distribution. Similar reef geomorphologies, high-energy environments, and the limited watershed drainage for both of the regions explain these similarities. Higher energy waves force the sub-environment >10 m depth into waters deeper than our depth of imaging, preserving antecedent topography in preference to reef-controlled morphology. This increases the availability of depressions that would normally be grown over or reshaped by reef accretion, and reduces the availability of those linear features formed as the reef’s response to hydrologic conditions. Limited watershed drainage also reduces the presence of paleo-channels within regions. The end result is a restricted conduit system connecting an expansive sub-environment <10 m depth, dominated by antecedent topography, with offshore sand fields deeper than our detection ability.

The first order control in sand storage on the eastern coastline is general geomorphology of the reef (“wide reef” vs. “deep reef”). Wide and shallow back reefs with well-defined reef crests (“wide reef”) have more surface area covered by sand, while deeper fringing reefs (“deep reef”) and barrier reef fronts have less percent coverage. The second order control is energy environment on similar reef geomorphologies. Sand storage on the eastern shoreline is most prominent in the general reef morphology we call “medium-energy wide reef” (Table 4.6). The reef morphologies we call “medium-energy deep reef” and “high-energy deep reef” have decreasing sand surface coverage respectively (Table 4.6).
4.4.3.3 Western Shoreline

There is only one region, Waianae, on the western shoreline. This is a high-energy environment in the winter months as it receives direct and refracted north Pacific swell, but a low-energy environment in the summer months as it is protected from trade wind waves. The offshore sand field is present in our depth of imaging around the offshore mouths of palaeo-channels in the region. These offshore sand fields are positioned next to ragged scarps that are the seaward edge of a sub-environment <10 m.

Total percent sand coverage for Waianae region is between those of reef morphologies with wide and shallow back reefs and those with narrow and deep back reefs. Though the sand deposit class distribution and reef morphology are similar to Kailua region, the different energy environment allows for greater sand storage with offshore sand fields extending into shallower depths.

Sand deposits in this region are primarily channels and connected fields class, with seven major channel systems all connected to offshore sand fields. Undulations along the reef top allow sand storage in fields of all types as strong long-shore currents associated with north Pacific swell move sediments southeast down the coastline. The arid environment minimizes the presence of overly large karst depressions. However, those features developed as antecedent topography are well preserved in this seasonally high-energy environment, so karst features such as individual dolines or small uvalas are still present within the region. It is possible the ragged scarp, the shoreward limit of most of the shallow offshore sand fields, is inherited from previous sea level transgressions, MIS 7, MIS 5, or a combination of the two. Combine the preservation of several generations of sub-aerial exposure with a seasonally high-energy environment, and sand
storage in Waianae region, more than any other, is a product of its antecedent
topography. Offshore fields account for the moderately high percent coverage even with
the absence of a wide back reef.

This reef morphology and hydrologic energy environment, "seasonally high-
energy deep reef" (Table 4.6), stores considerably more sand than similar "deep reef"
morphologies on the eastern shoreline. This is a function of both hydrologic energy and
an arid environment.

Comparing sand storage patterns in our study area, we find there are five general
types of reef and hydrologic energy environments (Figure 4.8) controlling sand deposit
surface area, distribution, and shape measurements. In order of highest to lowest sand
surface coverage, they are the following: "low-energy wide reef" (i.e. Honolulu and
Keehi Lagoon regions), "medium-energy wide reef" (i.e. Lanikai and South of Laie Point
regions), "seasonally high-energy deep reef" (i.e. Waianae region), "medium-energy deep
reef" (i.e. Kailua and Kaneohe regions), and "high-energy deep reef" (i.e. Mokapu Point
and North of Laie Point regions).

4.4.4 Applicability to Other Reefs

Sand deposit shape and distribution in our study area is controlled by reef
g geomorphology and hydrologic environment. As such, we believe that the sand deposit
class structure should apply to other high volcanic islands, most continental fringing
reefs, and some atolls. One notable exception is that channels and connected fields might
not apply to barrier reefs or atolls that have limited watershed drainage, even during
periods of sea-level regression.
The five general reef types inferred during Discussion are defined by sand deposit distribution, percent sand coverage, reef geomorphology, and hydrologic environment. We believe these general reef types should apply to all reefs with similar geomorphology and hydrologic environments.

4.5 CONCLUSIONS

1. We infer that first order control on sand storage is reef geomorphology ("wide reef" vs. "deep reef"), and second order control is hydrologic energy within the environment ("low-energy," "seasonally high-energy," "medium-energy," and "high-energy").

2. Almost all surface sands are located in waters less than 10 m depth and in deposits that cross the 10 m contour. We infer this to result from the sub-environment <10 m depth precluding closure of depressions by modern reef accretion, and conduit systems between nearshore and offshore sand deposits acting as storage basins. This is also the environment for greatest sediment production.

3. Highest percent reef coverage is within the channels and connected fields class. "Major channels" and "unchannelized drainage" subclasses, both in the sub-environment crossing 10 m, account for almost all of this class's surface coverage. We believe these two subclasses provide the connectivity between nearshore and offshore sand fields because they act as conduits within the reef's sediment system, linking nearshore zones of sediment production with regions of
sand storage. These channels need to be unbroken, or without outcrops across and above their channel walls, to be most effective.

4. Highest percent sand storage is in reefs with offshore sand fields and some wide and shallow back reefs, in low energy environments (Honolulu and Keehi Lagoon). Second highest coverage is in reefs without offshore fields but extensive wide and shallow back reefs, in moderately high-energy environments (Lanikai, South of Laie Point). Third highest coverage is in reefs with offshore fields, but without wide and shallow back reefs, in seasonally high-energy environments (Waianae). Reefs without offshore fields and wide and shallow back reefs have the least sand coverage, though they can be further separated by energy level of their environments: moderate high (Kailua, Kaneohe), and high (Mokapu Point, North of Laie Point).

5. We found total percent sand coverage to be highly indicative of general reef morphology and annual energy in an environment. Sand deposit class distribution and mean sand deposit shape measurements (glyphs) are helpful in identifying patterns associated with environmental factors.

6. The sand deposit classification system we have developed will easily export to other high volcanic islands. It should perform well on continental shelf and wide barrier and fringing reef settings such as the Caribbean and Great Barrier Reef. However it may not perform as well in atoll settings where watersheds are absent and the fore reef is quite steep in comparison to Oahu’s fringing reef.

7. The southern shoreline of Oahu is the most sand rich area on the island. Sediment productivity rates, a function of hydrologic climate and available sediment
production space, are high as a result of its exposure to refracted trade wind swell and south Pacific swell. High-energy hurricane waves and anthropogenic effects aid by providing temporally short term, but high volume increases in sediment production.

8. Offshore fields on the eastern shoreline are deeper than our depth of imaging. We believe significant variation between this side of the island and the others is the direct result of exposure to trade wind waves, which could be linked to increased depth for offshore sand fields.

9. Distinction of sand deposit classes is a non-trivial process. Class structures need to have significant numerical boundaries within the shape measurements that corroborate well with physical boundaries within the geologic settings. As the data is unimodal, use of a supervised classification algorithm is necessary and numerical boundary placement is an iterative process.

10. We found sand identification through remotely sensed data to be faster and more accurate than hand digitizing. However, the process needs to be controlled by the analyst. Some hand digitization is needed to fill gaps in the data.
Chapter 5

CONCLUSIONS

My research is focused on explaining the locations, characteristics, patterns, and relationships of carbonate sand deposits. My study area, Oahu, Hawai'i, is chosen as representative for fringing reefs on high volcanic islands in the tropics. However, the scheme we develop for characterizing sand deposits should be applicable on a far broader range of reef types than this specific one.

Initial work developed remote sensing techniques for rapid identification of sandy substrate across large areas of the reef. These techniques, when applied to reefs with either homogenous (Chapter 2) or heterogeneous (Chapter 3) water bodies, will allow for accurate identification of sandy substrate. This is a major step for efficient analysis of nearshore sand deposits, as these results will be already be geo-referenced to the initial remotely sensed data, creating the base layers of a GIS.

Chapter 4 outlines a classification structure for nearshore sand deposits using shape measurements for each deposit. This structure, created to identify specific shapes associated with reef geomorphologies, should be exportable to all other reefs with similar geomorphology and hydrologic environments. A product of this research is a generalization of reef types associated with two factors, and sand storage characteristics. These five reef types are the culmination of this research, as they relate patterns in sand storage to environments they are found in.

Ultimately, this research is the first major step toward improved understanding of the relationship between sandy substrates on reefs and the geologic, geomorphic, hydrologic, and ecologic environments they are a product of.
REFERENCES


APPENDIX 1: TABLES

TABLE 2.1 Confusion Matrix for training classes.

<table>
<thead>
<tr>
<th>Thematic Map Classes</th>
<th>Training Set Classes</th>
<th>User’s Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sand</td>
<td>Not Sand</td>
</tr>
<tr>
<td>Sand</td>
<td>59,835</td>
<td>397</td>
</tr>
<tr>
<td>Not Sand</td>
<td>1488</td>
<td>51,120</td>
</tr>
<tr>
<td>Producer’s Accuracy</td>
<td>97.57%</td>
<td>99.23%</td>
</tr>
</tbody>
</table>

Normalized Total Error: 0.0039607
Maximum Individual Error: 1.6830440
Total Learning Cycles: 1222

TABLE 2.2 Confusion Matrix for test classes.

<table>
<thead>
<tr>
<th>Thematic Map Classes</th>
<th>Test Set Classes</th>
<th>User’s Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sand</td>
<td>Not Sand</td>
</tr>
<tr>
<td>Sand</td>
<td>2,881</td>
<td>4</td>
</tr>
<tr>
<td>Not Sand</td>
<td>341</td>
<td>6,444</td>
</tr>
<tr>
<td>Producer’s Accuracy</td>
<td>94.52%</td>
<td>99.93%</td>
</tr>
</tbody>
</table>
TABLE 4.1 Shape measurements and descriptions.

<table>
<thead>
<tr>
<th>Area</th>
<th>PixelCount × (2.4m)$^2$</th>
<th>Converts pixel count to square meters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Orientation</td>
<td>Relative to histogram peak orientation</td>
<td>Each study region is adjusted so that a histogram peak of all sand deposits is at zero degrees, and all orientations are within ±90°, normalizing for all regions.</td>
</tr>
<tr>
<td>Form Factor</td>
<td>$\frac{4 \times Area \times \pi}{(Perimeter)^2}$</td>
<td>Degree of rugosity around the perimeter of each sand deposit, when compared to an equal area circle’s perimeter.</td>
</tr>
<tr>
<td>Roundness</td>
<td>$\frac{4 \times Area}{\pi \times (MajorAxis)^2}$</td>
<td>Comparing sand deposit area to a circle with radius equal to the deposit’s major axis.</td>
</tr>
<tr>
<td>Solidity</td>
<td>$\frac{Area}{ConvexArea}$</td>
<td>How full a sand deposit is, compared to a smooth shape whose perimeter intersects the outer points of the sand deposit’s perimeter.</td>
</tr>
<tr>
<td>Eccentricity</td>
<td>$\sqrt{1 - \left(\frac{MinorAxis}{MajorAxis}\right)^2}$</td>
<td>Measures elongation of a sand deposit within the range from a circle (0) to a line (1).</td>
</tr>
</tbody>
</table>
TABLE 4.2 Sand deposit class descriptionis.

<table>
<thead>
<tr>
<th>CLASSES</th>
<th>DESCRIPTIONS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>channels and connected fields</strong></td>
<td>Paleo-stream channels typically starting at or near the shoreline or a nearshore sand field and extending to an offshore sand field. These are highly complex, very elongate, non-rounded, open structures that cover large surface areas.</td>
</tr>
<tr>
<td><strong>complex fields and very large depressions</strong></td>
<td>Large sand fields made complex by their size, long perimeter, great number of outcrops, and rugged interaction with fringing substrate. Complex fields and very large depressions are significantly more rounded and solid than channels and connected fields. Large groups of interconnected depressions are also included in this class.</td>
</tr>
<tr>
<td><strong>large depressions and fields</strong></td>
<td>Large openings in the reef with steep sides, and fields smaller, less complex, and more solid than complex fields and very large depressions. These depressions likely result from solution basins and blue holes filling with available sands. Though original depressions were formed as dolines, uvalas, and possibly poljes (e.g. Ritter et al., 2002) during subaerial exposure, modern shape and orientation are likely due to coalescing and reshaping of depressions by modern hydrographic conditions. Medium sized fields also fit into this class.</td>
</tr>
<tr>
<td><strong>linear deposits</strong></td>
<td>Sands in a linear and fairly simple shape. These fill in linear depressions in the reef, usually in spur and groove, ridge and runnel, or furrow morphologies. They are also elongate bands extended by current and wave energies across the reef top.</td>
</tr>
<tr>
<td><strong>small depressions and simple fields</strong></td>
<td>Depressions are individual dolines or small uvalas. Fields are very simple fields, often filling in minor swales or undulations on the reef. Similar to those in large depressions and fields, except small areas with much simpler shapes. The average size limit is around 140 m², so they are only small by relative terms.</td>
</tr>
</tbody>
</table>
TABLE 4.3 Confusion matrix for substrate discrimination.

<table>
<thead>
<tr>
<th>Thematic Map Classes</th>
<th>Test Set Classes</th>
<th>User’s Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sand</td>
<td>Not Sand</td>
</tr>
<tr>
<td>Sand</td>
<td>17,608</td>
<td>81</td>
</tr>
<tr>
<td>Not Sand</td>
<td>470</td>
<td>17,639</td>
</tr>
<tr>
<td>Producer’s Accuracy</td>
<td>97.8%</td>
<td>99.5%</td>
</tr>
</tbody>
</table>

TABLE 4.4 Confusion matrix for sand deposit training classes.

<table>
<thead>
<tr>
<th>Thematic Map Classes</th>
<th>Training Set Classes</th>
<th>User’s Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>channels and connected fields</td>
<td></td>
</tr>
<tr>
<td>channels and connected fields</td>
<td>15</td>
<td>3</td>
</tr>
<tr>
<td>complex fields and very large depressions</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>large depressions and fields</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>linear deposits</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>small depressions and simple fields</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Producer’s Accuracy</td>
<td>100%</td>
<td>80%</td>
</tr>
<tr>
<td>class</td>
<td>example</td>
<td>glyph</td>
</tr>
<tr>
<td>-----------------------------------</td>
<td>---------</td>
<td>-------</td>
</tr>
<tr>
<td>channels and connected fields</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>500m</td>
</tr>
<tr>
<td>complex fields and very large depressions</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>500m</td>
</tr>
<tr>
<td>large depressions and fields</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>500m</td>
</tr>
<tr>
<td>linear deposits</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>500m</td>
</tr>
<tr>
<td>small depressions and simple fields</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>500m</td>
</tr>
</tbody>
</table>
TABLE 4.6 Five general reef types, regional environments, and sand storage characteristics.

<table>
<thead>
<tr>
<th>General reef type</th>
<th>Hydrologic energy environment</th>
<th>Reef geomorphology</th>
<th>Key sand storage</th>
</tr>
</thead>
</table>
| **Low-energy wide reef** | South Pacific swell (summer)  
   0.3-1.8 m heights  
   12-20 s periods | Back reef <0.5 km wide (wider before artificial alteration)  
   <1-3 m deep | “major channels”  
   “unchannelized drainage”  
   “fields with steep boundaries”  
   “open fields”  
   “reefal strandlines”  
   “radial lineations” |
| | Kona storm waves (9% of year)  
   3-4.5 m heights  
   6-10 s periods | Variable presence of distinct reef crest  
   0-3 m deep | MOST ABUNDANT SAND |
| **Medium-energy wide reef** | Trade wind waves (90% summer, 55-65% winter)  
   1.2-3 m heights  
   4-10 s periods | Back reef >0.5 km wide  
   <1-3 m deep | “major channels”  
   “fields with steep boundaries”  
   “open fields”  
   “reefal strandlines”  
   “large depressions” |
| | Refracted north Pacific swell (winter)  
   1.5-4.5 m heights  
   12-20 s periods | Distinct shallow reef crest  
   1-3 m deep | 2nd MOST ABUNDANT SAND |
| **Seasonally high-energy deep reef** | Direct and refracted north Pacific swell (winter)  
   1.5-4.5 m heights  
   12-20 s periods | Back reef variable width from <0.5 km to >1 km wide, typically narrow  
   2-10 m deep | “major channels”  
   “fields with steep boundaries”  
   “linear deposits”  
   “small depressions” |
| | Direct and refracted south Pacific swell (summer)  
   0.3-1.8 m heights  
   12-20 s periods | Generally deep reef crest  
   3-15 m deep | 3rd MOST ABUNDANT SAND |
| | Kona storm waves (9% of year)  
   3-4.5 m heights  
   6-10 s periods | | |
| **Medium-energy deep reef** | Trade wind waves (90% summer, 55-65% winter)  
   1.2-3 m heights  
   4-10 s periods | Back reef variable width generally  
   >0.5 km  
   3-10 m deep | “major channels”  
   “transition channels”  
   “very large channels”  
   “large depressions” |
| | Refracted north Pacific swell (winter)  
   1.5-4.5 m heights  
   12-20 s periods | Deep reef crest >8 m deep | 4th MOST ABUNDANT SAND |
| **High-energy deep reef** | Direct and refracted north Pacific swell (winter)  
   1.5-4.5 m heights  
   12-20 s periods | Back reef >0.5 km wide  
   >3 m deep | “major channels”  
   “sand-starved channels”  
   “large depressions”  
   “small depressions”  
   “linear deposits” |
| | Trade wind waves (90% summer, 55-65% winter)  
   1.2-3 m heights  
   4-10 s periods | Deep reef crest >5 m deep | LEAST ABUNDANT SAND |
APPENDIX 2: FIGURES

FIGURE 2.1 CASI image of Gezirat Siyul, Egypt with inset map of Red Sea. Red and green pixels are the training class data for "sand" and "not sand" classes respectively. Yellow and magenta pixels are the test data for "sand" and "not sand" classes.
FIGURE 2.2 Spectral plot of all training pixels. Axes are blue and green channel DN values.

FIGURE 2.3 Spectral plot of all test pixels. Axes are blue and green channel DN values.
FIGURE 2.4 Classified image for Gezirat Siyul, Egypt. Blue area is masked out. Green pixels are identified as "not sand" class, and remaining image is identified as "sand" class.
FIGURE 3.1 Scatter plot of model data explaining decorrelation method. Each model has depth as x-axis and intensity as y-axis. A) shows model data for three different reflectors with intensity values. B) is same reflectors with ln-transformed intensity values. C) is same reflectors after rotation.

A

B

C

○ low albedo
□ middle albedo
◇ high albedo

depth

depth

depth
FIGURE 3.2 A) Map of Oahu, Hawai‘i, with B) color satellite image and C) bathymetry map for Kailua Bay, Oahu, Hawai‘i. Yellow line in B represents the sand transect pixels chosen to model the band pair rotation.
FIGURE 3.3 Scatter plots for sand transect pixels. Each point is an individual pixel, each pixel is represented in the blue, green, and red band with depth values on the x-axis and intensity values on the y-axis. A) is the sand transect pixels with initial intensity values, B) is ln-transformed values, and C) is rotated values.
FIGURE 3.4 Gray scale images of color bands before and after decorrelation from depth. A, B, and C are the before images for blue, green, and red bands respectively. D, E, and F are the after images for blue, green, and red respectively.
FIGURE 4.1 Bathymetry and topography of Oahu, Hawaii, coastal zone with study regions outlined. A) is the Waianae region, B) is North and South of Laie Point regions, C) is Honolulu and Keehi Lagoon regions, and D) is Lanikai, Kailua, Mokapu Point, and Kaneohe regions.
FIGURE 4.2 Section of Kailua Bay showing A) decorrelated color band and B) classified image.
FIGURE 4.3 All classified sands (black areas) displayed alongside a topographic map of Oahu. A) is Waianae region, B) is North and South of Laie Point regions, C) is Honolulu and Keehi Lagoon regions, and D) is Lanikai, Kailua, Mokapu Point, and Kaneohe regions.
FIGURE 4.4 Bar plots of: A) total sand area by region, and B) total percent sand coverage by region with percent coverage listed on each bar.

![Bar plots of sand area and percent coverage](image)

FIGURE 4.5 Glyph plots displaying mean sand deposit shape measurements for each region.

![Glyph plots of sand deposit shapes](image)
FIGURE 4.6 Bar plots showing sand deposit class distribution for each region and all regions combined. Percent coverage is listed above each bar.
FIGURE 4.7 All channels and connected fields class (black areas) displayed alongside a topographic map of Oahu. A) is Waianae region, B) is North and South of Laie Point regions, C) is Honolulu and Keehi Lagoon regions, and D) is Lanikai, Kailua, Mokapu Point, and Kaneohe regions.
APPENDIX 3: FUSED BAND ROTATION

This appendix is summery of Chapter 6.1, "Principal Component Transformation," in Richard and Jai (1999). They use Principal Component Analysis (PCA) as a method for rotating multiple image bands to reduce data channels and noise (our Chapter 2 rotation). Though we use the same technique, our rotation combines image and depth band pairs to remove the relationship between light loss and water depth (Chapters 3 and 4). Either way, correlation between bands is removed as part of the rotation process.

PCA is a linear rotation of band data. These data are shifted to a new origin, rotated according to a model 2 (perpendicular) regression line, and projected onto their new axes. This does not, however, change their relationship to each other. Each pixel's values will hold the same relationship with every other pixel's values, before and after rotation.

Step one is to shift all data to a new origin. The new origin is found by subtracting the mean vector $m$ for all bands $k$ from the $n$ pixels in the image.

$$m = \frac{1}{n} \sum_{k=1}^{n} X_k$$

Step two is to use the covariance matrix $\sum_{x}$ as an approximation for the spread of the data in $k$ bands.
The advantage of using the covariance matrix for describing the spread of the data is that the relationship between the off-diagonal values and the diagonal values is a function of the correlation between bands. In other words, bands that are highly correlated will have high shared off-diagonal values (covariance) relative to their individual (variance) diagonal values. And if there is little correlation between the bands, their shared off-diagonal values (covariance) will be small compared to their individual diagonal values (variance).

The value of PCA transformation is that the new band data will be decorrelated, or share no covariance. In other words, after rotation all off-diagonal (covariance) values for the new data set will be zero. For our purposes, this means that the new image band will have no covariance, and no correlation with the depth band. Thus light intensity, as measured within the digital image, will not change in relationship to depth change.

We wish to find the linear transformation \( G \) (PCA transformation matrix) that will project the pixel values \( x \) into a new coordinate system with new pixel values \( y \), with the constraint that the new covariance matrix will be diagonal (covariance values = 0).

\[
y = Gx
\]

We know that the new mean vector will be related to the old mean vector by this transformation.
\[ m_y = Gm_x \]

Thus we can create the equation for covariance in our new data projection using this transform and solve it for a diagonal covariance matrix \( \sum_y \).

\[ \sum_y = G \sum_x G' \]

In this case the off-diagonal values in \( \sum_y \) are the eigenvalues. Eigenvalues are the amount of variance in each new band, with all diagonals summing to 100% of the variance for all bands. These values will be ordered so that the first diagonal value will be highest (containing the most variation in the data set) and each successive diagonal value will be a smaller value (less variance) than the one prior. \( G \) is a transformation matrix containing eigenvectors as its column data. These eigenvectors are the new unit vectors for each axis. The product will be eigenbands. Eigenbands will contain the new pixel values \( y \) for \( k \) new bands, and they will have no correlation (covariance = 0) with each other.

In our method (Chapters 3 and 4) two eigenbands will be created. One will be depth related (original bathymetry and light attenuation) and the other will be decorrelated image intensity. The second band, decorrelated image intensity, allows us to map out changes in substrate (reflector) without the effects of light attenuation within the water column.