Autoclassification versus Cognitive Interpretation of Digital Bathymetric Data in Terms of Geomorphological Features for Seafloor Characterization

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ABSTRACT


The determination of seafloor geomorphological features has always been a difficult task, and it was not until the advent of marine remote sensing techniques that seafloor features could be accurately discerned. Airborne acquisition of digital bathymetric data provides a wealth of information that can be interpreted in different ways. This paper considers the pros and cons of computerized autoclassifications versus cognitive interpretations of seafloor features. The continental shelf off the southeast Florida coast contains LADS (laser airborne depth sounding) surveys that are here used to compare and contrast automated classifications of bathymetry with cognitive differentiation of marine geomorphological features. There are advantages and disadvantages associated with each approach, and the choice of methods depends on the purpose or goals of the project. Once seafloor features have been cognitively discerned from enhanced, color ramped, and vertically exaggerated bathymetry, machine classifications can be compared with known units. Using ArcGIS® ArcMap software, five- and seven-class unsupervised isocluster autoclassifications were found to moderately represent known bottom topography, whereas the interactive supervised autoclassification closely approximated cognitively discerned bathymetric patterns. Hand-drawn or digitized cognitively derived maps were more generalized than supervised computerized classifications based on training fields. Overall, both methods were found to be beneficial approaches, as they complement each other.

ADDITIONAL INDEX WORDS: Coastal classification, benthic environments, coral reef, LIDAR, laser airborne depth sounding, coastal sediments, continental shelf, Florida Reef Tract.

INTRODUCTION

Although there are many different methods for classifying seafloor features, most have a special purpose with specific goals that rely on the product of the survey technique (e.g., Achatz, Finkl, and Paulus, 2009; Brock and Purkis, 2009; Chust et al., 2008; Collins, Penley, and Monteys, 2007; Finkl, 2004a,b; Finkl and DiPrato, 1993; Greene et al., 1999; Mayer, 2006; Pittman, Costa, and Jeffrey, 2013; Walker, Riegl, and Dodge, 2008). The continental shelf off the southeast Florida coast has been intensively studied using remote sensing techniques since the 1960s. Duane and Meisburger (1969), for example, conducted reconnaissance seismic reflection profile surveys that for the first time outlined the basic framework of shelf features. Their seismic reflection profiles showed spatial distributions of shore-parallel coral reef tracts, interreefal sediment-filled troughs, and outcrops of carbonate bedrock. More recent LIDAR (light detection and ranging) surveys (2001 and 2008) in the form of LADS produced remarkably detailed depictions of shelf bathymetry. These digital data were amenable to color ramping where tonal variations could be keyed to depth. The resulting combination of texture, tone, and pattern in the digital data provided a basis for cognitive (manual) interpretation of seafloor features. A series of maps showing spatial distribution patterns of seafloor features was prepared by Finkl and Andrews (2008, 2009), where they recognized marine landforms and drowned subaerial forms. These cognitively derived (manually interpreted) maps were composed by hand and based on visual inspection; afterward, the mapping units were transferred into ArcGIS software. Because the LADS data is in a digital format, it is also possible to attempt autoclassification of bathymetry. This paper examines the ability to classify bathymetric patterns using automated computer routines. The results of unsupervised isoclustering and interactive supervised autoclassifications are then compared with previously prepared cognitive maps of seafloor features. The purpose of this effort was to evaluate the efficacy of autoclassification versus cognitive recognition in terms of geomorphological features for seafloor characterization.

Study Area

Two LADS surveys (2001 and 2002) were conducted along the southeast coast to include a shelf area of about 600 km² (Figure 1). These LADS 4-m resolution surveys were used to compile the cognitively interpreted maps of seafloor features. The present study area (cf. Figures 1 and 4) is a small subset offshore of the boundary between Broward and Miami-Dade counties, making up about 20 km². This small subset is used to illustrate the concept of autoclassifying LADS bathymetric data. This particular shelf area was selected because it...
contains a variety of landforms that were previously identified and mapped (Finkl and Andrews, 2008, 2009; Finkl and Banks, 2010; Finkl, Benedet, and Andrews, 2004, 2005a,b; Finkl et al., 2008). This being the case, the area provides a basis for comparing different mapping procedures.

**Purpose and Goals**

The purpose of this study is to compare autoclassifications of LADS digital bathymetric data with cognitively derived interpretations. Cognitive maps in general are based on memory of the physical (spatial) environment, the transformation of locational attributes, and decoding of information about relative locations, etc. (e.g., Berberoglu, Yilmaz, and Özkam, 2004; De Cola, 1989; Dobson and Dustan, 2000; Downs and Stea, 2005; Hochberg and Atkinson, 2000; Li and Yeh, 2004; Maritorena, Morel, and Gentili, 1994; Mumby et al., 1998; Yang et al., 2009; Zhu and Cai, 2007). In this case, the cognitive maps are based on knowledge of, recall, and recognition of geomorphic features as they occur in the landscape or subsea- scape. The effort is a simple one for comparison without prejudice or bias toward any method. Thus, the goal of this research was to see how cognitive and autoclassified bathymetric patterns compare. Such comparison does not assume one method was more correct or better than another, as they are all approximations of reality. The comparison was simply out of interest to see how different methodologies stack up one against the other. That is, the purpose was not to attempt to validate the accuracy of one method *versus* another but to compare results of different processes and see how their spatial distribution patterns correlate or correspond.

**METHODS**

The basic procedure was to select a subset of the overall LADS study area and compare the previously identified geomorphological features (as described by Finkl and Andrews, 2008, 2009; Finkl and Banks, 2010; Finkl, Benedet, and Andrews, 2005a,b; Finkl et al., 2008) with auto-generated classifications of the same area. In order to determine whether autoclassification algorithms would produce results comparable to cognitively interpreting, a series of autoclassifying tests was performed in ESRI’s ArcGIS ArcMap. The computerized classification of the LADS digital bathymetry was divided into two parts, unsupervised isocluster and interactive supervised methodologies. Several iterations of both procedures were run in an attempt to discern comparability with known seafloor geomorphological distribution patterns. Pixel digital numbers (DNs) were based on variations in color derived from the color ramp that was applied to the DEM. Critical to this aspect of the procedure was the selection of the number of classes to be discriminated by computer runs. Initial experimentation showed that a large number of autoclasses produced patterns that were not comparable with previously derived geomorphological maps. Iterations using a dozen or so classes were used to produce recognizable patterns in interactive supervised classifications, whereas unsupervised isocluster autoclassifications required a number of classes fewer than 10. Details of the autoclassification procedures are briefly summarized here.

**Unsupervised Isocluster Autoclassification Method**

Within ArcMap, the Image Classification toolbar was activated, and an unsupervised isocluster autoclassification was performed on a specific subset of the overall LADS study area. Once the appropriate input raster (composite of the RGB bands) was selected and the output-classified raster was renamed in the proper geodatabase, the number of classes was assigned according to the same number of features interpreted from cognitive processes. For example, in the LADS subset study area, where 14 geomorphological features were cognitively interpreted, the number of untrained classes assigned for the unsupervised isocluster autoclassification was 14. However, as mentioned above, an untrained class count greater than 10 for unsupervised isocluster analysis of the LADS bathymetry generates unusable results (cf. Figure 6). Instead, a second and third unsupervised isocluster classification analysis was performed with five and seven untrained classes, respectively. Once the unsupervised isocluster autoclassifications were performed, individual output rasters were saved as Tiff image files and imported as layers into ArcMap adjacent to the raw LADS images. This additional step of saving out to a Tiff is not necessary to compare in GIS because the information can be compared with the output geodatabase results directly. The procedure of saving to a Tiff file was performed so the image could be used in other programs and as a backup. These displays were then exported and visually compared with the cognitively interpreted displays of the same LADS imagery scenes to help determine the correlation of this autoclassification.

Figure 1. Location diagram showing the original LADS survey area along the southeast Atlantic coast of the Florida Peninsula. The detailed area of investigation is marked by the red outline.
Interactive Supervised Autoclassification Method

Within ArcMap, the Image Classification toolbar was activated, and an interactive supervised autoclassification was performed on the same LADS subset study area as the unsupervised isocluster method. Once an individual LADS scene was selected in the drop-down window from the Classification toolbar, the Training Sample Manager window was opened. Training sites were then established for the interactive supervised classification to correspond to the pixel patterns used previously for cognitive interpretation of the seafloor features. For example, in the LADS subset study area, where 14 geomorphological features were cognitively interpreted, 14 training sites were established for the interactive supervised classification to best match the visual criteria used when interpreting cognitively. Selection of these various training fields is shown in Figure 2. The training fields were variable in shape depending on the nature of the geomorphological landform pattern that was selected. It was recognized that selection of training fields was critical, as the field had to be representative of the type of feature or pattern that was to be autoclassified. In this manner, the operator must accurately train the program to recognize these features or patterns. The training fields were thus carefully selected in an attempt to capture the best examples of the features to be mapped. After the interactive supervised classifications were performed, individual output rasters were saved as Tiff image files and imported as layers into ArcMap adjacent to the raw LADS images. These displays were then exported and visually compared with the cognitively interpreted displays of the same LADS imagery scenes to help determine the correlation of this autoclassification.

RESULTS

Resultant maps from the autoclassification of LADS digital bathymetric data are shown in Figure 3. This diptych shows on the left panel the result of unsupervised isocluster classification using seven untrained classes. The right panel shows spatial distribution patterns based on an interactive supervised classification using 14 trained classes. A larger number of classes (i.e. greater than 10) used in the unsupervised isocluster autoclassification resulted in spatial distribution patterns that grossly misrepresented known seafloor geomorphology.

Figure 4 shows a subset of a larger section of the LADS survey area that was cognitively interpreted and illustrates the results of autoclassification compared with cognitive mapping. In this sense, the cognitively interpreted units are used as a kind of control for assessing the efficiency of the machine classifications.

Results of color ramping to vertically exaggerate LADS bathymetric data are shown in Figure 5, left panel. The right panel of this diptych exhibits a product of cognitive mapping of seafloor features on the shelf. The purpose of the diptych is to
show how the cognitively derived mapping units compare with the color ramped LADS bathymetry. The right panel is the result of cognitively interpreting submarine landforms along the continental shelf.

The triptych in Figure 6 shows the results of several unsupervised isocluster autoclassifications using five-, seven-, and 14-class units, respectively, for the LADS subset area. The left and middle panels have their own sets of advantages and disadvantages, whereas the right panel based on 14 classes cannot be used for any method of comparison. Both left and middle panels correlate or agree with the control in terms of differentiating major geomorphological features on the shelf. The results of the five- and seven-class unsupervised isocluster autoclassifications are thus summarized by comparison with color ramped LADS bathymetry and cognitively derived classification units in what follows below.

Figure 7 shows the results of an unsupervised isocluster autoclassification using seven untrained classes, right panel of the diptych, compared with the color ramped LADS bathymetry (left panel). Cognitive interpretation of submarine landforms is provided in Figure 8, left panel of the diptych, with the same unsupervised isocluster autoclassification as contained in Figure 7 in the right panel. The results of both procedures (cognitively derived units and delineations obtained from unsupervised isocluster autoclassification) show a gross correspondence of patterns with structural sandflats (light blue color) and the nearshore bar and trough system (green, purple, and orange colors) defined along with rock outcrops and coral reefs. However, the orange and green colors confuse coral reefs with rock outcrops and parts of the nearshore bar and trough system. The legend for the cognitive mapping units is given in Figure 13. It is not possible to provide classification units for the unsupervised isocluster autoclassification because they overlap a range of bottom types.

Figure 9 is a diptych that compares a product of unsupervised isocluster autoclassification using seven untrained classes (right panel) with color ramped LADS bathymetry (left panel). The increase in the number of classes used here from five to seven provides better discrimination of bathymetric patterns, but reference to Figure 10 is required to assess the relative value of the seven-class unsupervised isocluster autoclassification (right panel) when compared with the cognitively derived units (left panel). The results of this unsupervised machine autoclassification are useful in the differentiation of the nearshore bar and trough zone into four units (black, green, red, and blue colors) and the structural sandflats into two units (yellow and pink units). Rock outcrops and coral reefs are confused (red, green, and black colors), but offshore sandflats and diabathic channels are broadly outlined. The seven-class unsupervised isocluster classification has advantages over the five-class unsupervised isocluster autoclassification, but there are still problems of miscorrelation of seafloor geomorphological features.
The results of the interactive supervised autoclassification using 14 trained classes is shown in Figure diptychs (two panels) 11 and 12, where the machine classification is compared with the color ramped LADS bathymetry and cognitively derived classification units, respectively. The more complex patterns of the interactive supervised autoclassification (right panel of Figure 12) show a closer approximation of the cognitively derived landform patterns in the left panel of the diptych. The results here show a comparative advantage of using training fields to better define bathymetric patterns by machine classification. The mauve color in the right panel of the diptych encompasses structural sandflats and offshore sandflats. There is, on the other hand, an advantage to showing the spatial distributions of thicker sand veneers on the structural sandflats (disjunct pink colors) by virtue of texture, tone, and pattern of sandy areas. Coral reef subcrop, diabathic channel fields, offshore sandflats, and overwash deposits are fairly discriminated. The problem of rock outcrops and coral reefs occurring in the same color remains.

Finally, in Figure 13, the interactive supervised autoclassification is merged with the cognitively derived landform patterns as an overlay. Legends for both maps are provided for ease of reference. It should be noted that names of the training units (provided in the Training Sample Manager) are derived from the cognitive mapping and serve as interpretation guidelines when applying the interactive supervised autoclassification method. The legend for the cognitively derived mapping units is provided here. By reference to both legends, it is possible to at once appreciate the broad correspondence and mismatch of supervised autoclassed units with cognitive units. Details of map unit conformity are given in the summary of Figure 12. Reasons for correspondence or discordance of the
different types of mapping units are suggested in the analysis that follows.

ANALYSIS

Comparison of the autoclassifications with a control, in this case the cognitively interpreted maps, shows a gross correspondence between the unsupervised isocluster autoclassification and the control. Detailed comparisons are more complicated as seen along the shore, for example, where three units are differentiated for the single larger bar and trough units on the cognitive map (Figure 4). Comparison of the subdivision of the nearshore zone using five (Figure 3, left panel), seven (Figure 3, right panel), and 14 untrained classes (Figure 6, right panel) shows greater detail where seven units are differentiated. The texture, tone, and pattern attributes of the LADS bathymetry are detected in the unsupervised isocluster classification, suggesting there is a basis for discerning discrete landform units. Ground truthing would be required for verification of the units identified in the unsupervised isocluster autoclassification, but in situ familiarity with the conditions on the ground would suggest a surf zone unit close to the shore, crenulated bars alongshore, and fans or sediment splays seaward. And based on the middle panel of Figure 6, there appear to be other discrete landform units not yet identified. These kinds of units, as well as unknown units, are visible in the color ramped LADS bathymetry but were not differentiated in the cognitive inspections due to scale restraints mapping at 1:600.

Rock outcrops and inner coral reef tracts were differentiated in the five- and seven-class autoclassification, but they were confused with seaward segments of the bar and trough system along the shore, and then they were massively confused offshore with a wide range of features ranging from interreefal sand flats to coral reefs (cf. Figures 7 and 9). Compared with the left panel of Figures 3 and 6, the middle panel based on seven classes appears to better differentiate variations in structural sandflat areas (cf. Figure 10) because there are variations in the distributions of yellow and pink tones. The pinkish tones appear to correlate with a smoother (flatter) bottom topography, suggesting sand cover on structural sandflats. Offering a value judgment as part of the analysis, it was perceived that parts of the unsupervised isocluster autoclassification did not clearly differentiate structural sandflats from nearshore and offshore sandflats but did delineate rock outcrops, subcrops (rock buried by a thin veneer of sand), and coral reefs. That is, these five- and seven-class units generally corresponded with the cognitive map, with the exception of misclassification along the seaward margin of the bar and trough shore zone, where the same color is used for both rocky seafloor and sand bottom (cf. Figures 7–10). Observation of this correspondence between mapping units, including observation of misclassified units, thus suggested the advisability of conducting interactive supervised autoclassifications to improve the interoperability of classification and verification with the control.

Observation of the interactive supervised autoclassification showed more complex spatial distribution patterns that in
many ways corresponded to parts of the cognitive map, as shown in Figure 13. Although this map is at first somewhat confusing because it merges two different approaches for depicting seafloor geomorphology, more careful study (compared with a cursory glance) shows many important interrelationships. Starting at the shore and moving seaward, it is observed that the interactive supervised autoclassification matches the cognitive interpretation. Additional detail is provided in the form of distributions for nearshore sandflat, offshore sandflat, and hard-bottom outcrop.

The lack of contextual data in the interactive supervised autoclassification geographically misplaces the offshore sandflat unit nearshore. Editing is required to reclassify the offshore sandflat units adjacent to the bar and trough system as nearshore sandflats. This misclassification occurs because nearshore and offshore sandflats show the same texture, tone, and pattern as the color ramped LADS DEM. The misclassification is not a failure of the interactive supervised autoclassification but a cognitively derived decision to separate sandflat occurrences geographically.

The distribution of offshore sandflats (see legend in Training Sample Manager in Figure 13) obtained in the interactive supervised autoclassification substantially improves the cognitive delineation of ridge field outcrop and subcrop, as well as occurrence of hard-bottom subcrop. The presence of disjunct sandflat units within the ridge field outcrop and subcrop delineations was recognized during the cognitive mapping process, but it was not possible to provide the level of detail acquired from the interactive supervised autoclassification. In fact, the term "subcrop" was invoked in the name of the mapping unit delineation to convey the idea that the bedrock was partially covered by sand veneers. By providing training fields for sandflats, it was possible to display their spatial distribution to advantage. The information content of the resulting montage thereby materially enhances perception of hard-bottom and ridge fields covered by sand splays that form discrete sandflat units.

Moving farther cross-shore, it is seen that hard-bottom outcrop and coral reef are geographically confused because in spite of training fields, both features tend to display similar bathymetric texture, tone, and pattern. Contextual information, which is available in the cognitive mapping process, is lacking in machine classifications.

Coral reef subcrop is perhaps better defined in the interactive supervised autoclassification, as it provides greater spatial definition than the cognitively drawn map. This observation is confirmed by comparing the patterns in the montage (Figure 13). The advantage to using training fields is emphasized here, as the distribution of coral reef subcrop is somewhat more extensive than originally mapped in the cognitive interpretation.

Diabathic channel fields occur seaward of the coral reef subcrop or are palimpsest (Figure 13). Although channel fields were recognized and cognitively mapped, the interactive supervised autoclassification increases the efficiency of discriminating detailed spatial distributions of these features.

Figure 6. Triptych (three panels) showing spatial distribution patterns derived from unsupervised isocluster analysis of the LADS bathymetry DEM using five classes (left panel), seven classes (middle panel), and 14 classes (right panel). The third panel shows that increasing the number of classes does not necessarily improve discrimination of this LADS DEM image.
Owing to the complex bathymetric patterns of diabathic channels, it was not possible to delineate all of them by hand. Machine classification in this case does a better job of showing details that could only be generalized by cognitive mapping.

Reef gaps are a good example of a morphological feature that requires contextual data for spatial definition. The reason for this difficulty is that reef gaps are composed of discrete morphologies that combine to produce this category. Because reef gaps are diabathic breaks in parabathic reef tracts, they are very distinctive features that are morphological and processually important to shelf sedimentary dynamics (e.g., Finkl, 2004b). The gaps are bounded by coral reefs on their north and south margins, but the east–west throat of the gap may contain, in part, sandflat, overwash deposits, or coral reef subcrop. These bathymetric features are thus complex and hard to autoclassify because they contain or combine other units. As seen in the montage (Figure 13), nearshore and offshore sandflats are identified in the gap throats by the interactive supervised autoclassification. The identification of sandflats in the reef gaps is not incorrect according to the rules of the training fields, but it is at odds with contextual information, at least in the case of nearshore sandflats.

Overwash deposits are more widely distributed according to the interactive supervised autoclassification. This is now possible through machine autoclassification, as they were somewhat difficult to cognitively determine by bathymetric texture, tone, and pattern when merging with offshore sandflats.

Shallow borrow areas correspond with those that were cognitively delineated in the control but get confused with offshore sandflats. The deep borrow area units are somewhat problematic in the interactive supervised autoclassification because they tend to merge with deeper water sandflats near the edge of the continental shelf. This complication is not surprising, as borrow are dredge pits located in sandflats. So, again, this is an example of the need for contextual information to qualify the mapping unit. The interactive supervised autoclassification correctly identifies the presence of sandflats that happen to also be borrow. The key to the delineation is the particular texture, tone, and pattern sequence in the color ramped LADS DEM.

**DISCUSSION**

There are many ways to evaluate the validity or accuracy of map products, however produced. Before the advent of modern computerized mapping and GIS, maps were validated by field checks and comparison with other maps that were known to be correct. Validation and accuracy assessment of computer-aided maps is achieved by a variety of statistical procedures and mathematical evaluation of self-tests. What is discussed here is the visual comparison of machine-classified maps versus cognitively derived maps, a simple procedure that is a measure of correspondence. The value of this experiment is considered in terms of pros and cons of an unsupervised isocluster autoclassification methodology and an interactive supervised autoclassification methodology compared with mapping units.
based on the ratiocinative powers of the human brain. The results of this process suggest future testing of the possibility of producing composite maps of digital LADS bathymetry.

**Rationale for Experimental Design**

Digital bathymetric data provide new opportunities to investigate the nature or character of seafloor topologies. The LADS data, for example, provide a dense sampling medium that can be manipulated to form a DEM of seafloor bathymetry. Elevations were exaggerated about 12 times to emphasize topographic differences in an effort to assist the cognitive interpretation process. A color ramp keyed to bathymetry was draped over the DEM with an assumed light source to the northwest (to produce shadows). The purpose of this procedure was to produce a colored representation of seafloor topography that would lend itself to visual inspection and consequent interpretation of bathymorphological features. This kind of observation and interpretation was heretofore not possible before the advent of LADS surveys. The sample density of these LADS surveys (4-m resolution) was sufficiently detailed to allow construction of maps that allowed interpretation of mesoscale geomorphological features (Finkl and Andrews, 2008, 2009; Finkl and Banks, 2010; Finkl, Benedet, and Andrews, 2004, 2005a,b; Finkl et al., 2008). This feat was in itself a major advance in the study of the southeast Florida continental shelf, and for the first time researchers were permitted comprehensive views of seafloor topologies.

Most recently it was hypothesized that the digital bathymetric data might be amenable to further scrutiny via automated classifications of the type applied to digital aerial and satellite images. Initial assumptions were that unsupervised classifications would be more or less useless for interpretation of seafloor features, as is largely the case with hyperspectral data. There are many reasons why hyperspectral data, usually measured with hundreds of narrow spectral bands about every 10 nm apart, have limited use for classificatory purposes in the marine environment. For example, in order to accurately obtain spectral signatures from hyperspectral remote sensing methods for different entities, such as different phytoplankton classes, zooxanthellae clades, or scleractinian (i.e. hard coral) species, one must first provide in situ spectral information. Without such information, the imagery cannot be interpreted, a function of the natural spectral variability being unknown.

One such effort took place at Buck Island, St. Croix, U.S. Virgin Islands, where hyperspectral data obtained by AVIRIS (airborne visible infrared imaging spectrometer) was used in response to a mass coral bleaching event in the Caribbean (Kruse, 2003). Kruse (2003) used the visible spectrum of AVIRIS light data reflecting off of the coral reef and the surrounding reef bottom in order to estimate the extent of the bleaching, as well as the overall health of the coral colonies. Even so, underwater handheld spectroradiometers first had to be used to measure the reflected light readings from bleached coral. Only then could hyperspectral imagery data be calibrated to the in situ reflectance readings for an accurate

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Figure 8. Comparison of a five-class unsupervised isocluster analysis (right panel) with cognitively interpreted geomorphic features on the shelf (left panel). This diptych shows generalization that occurs in maps hand-drawn at a nominal scale of 1:600 compared with greater detail that is acquired in autoclassification.
interpretation. Furthermore, special geometric and atmospheric correction techniques were required to recalculate hyperspectral image pixels with data values that correspond to reflectance from the precise locations of those pixels. However, the main disadvantage is that the nominal spatial resolution of hyperspectral data is necessarily lower in order to maintain an acceptable signal-to-noise ratio. This is simply a function of fewer available photons located in the narrow hyperspectral bands to interact with a sensor’s detector elements. Consequently, the end result provides very little image resolution to aid in the visual interpretation of the coastal environment. As stated in Lee and Carder (2005), a more cost effective multispectral sensor would be preferred over hyperspectral imagery when evaluating the major properties of coastal or shallow-water environments. Digital bathymetry does not retain these disadvantages, and there is thus a new opportunity to investigate the possibilities of autoclassification procedures. Perhaps surprisingly, our first attempts to classify the LADS bathymetric data showed some promise, and this investigation was therefore launched as an experiment.

As we proceeded with the experimental unsupervised classification, it was immediately appreciated that legends would be required for the units resulting from application of various algorithms. It soon became obvious that without a priori knowledge, it would be difficult to interpret the resulting categorizations. So, in order to facilitate the interoperability of the autoclassed maps, it was decided to compare them with spatial distributions that were already known. Fortunately, the LADS bathymetric data had already been cognitively interpreted, and maps of seafloor geomorphological units were prepared by Finkl and Andrews (2008, 2009); Finkl and Banks (2010); Finkl, Benedet, and Andrews (2004, 2005a,b); and Finkl et al. (2008). These maps could thus be used as a kind of control, or at least a reference base, to compare the results of autoclassifications. Our experiment was thus designed to conduct autoclassifications and compare the results with cognitively interpreted LADS bathymetric data. The scheme is not perfect in the sense that the result of autoclassification was compared with an interpretation, but there is no other alternative. In any case, from our point of view, a cognitive interpretation should take precedence over autoclassifications that lack input from collateral data and geographical perspective (spatial associations).

**Unsupervised Isocluster Autoclassification Methodology**

The efficiency of unsupervised pixel clustering is mainly dependent upon the visual properties of the image being classified. In this study, the original color ramped LADS bathymetric DEM does not offer a specific enough delineation of spectral signatures across the image. In other words, if too
many pixels with similar spectral properties are detected in multivariate space within the color ramped DEM, then the autoclassification cannot selectively assign different color values to represent the various seafloor landforms. This can be seen when 14 classes were used in the unsupervised isocluster autoclassification versus five and seven classes. Because the color ramped LADS DEM does not offer enough spectral contrast and there is no cognitive intervention when running an unsupervised isocluster autoclassification, when an increased number of classes is used, each class will inadvertently include a cluster of pixels that carry the same value. When the computer runs the unsupervised isocluster autoclassification and detects the same pixel-valued clusters throughout the color ramped LADS DEM, the same representative color is applied universally. This can be seen in the right panel of Figure 6, where one shade of green was used to classify the entire color ramped LADS DEM when using a 14-class unsupervised isocluster analysis. Conversely, by limiting the number of classes used to five and seven, the unsupervised isocluster autoclassification can separate out clusters with distinct pixel values more efficiently. The result can be seen in the left and middle panels of Figure 6, where applied representative colors more closely match that of the cognitive interpretation.

A potential solution to this problem would be to use a greater range of hues in the color ramp when it is applied to the LADS DEM. The range of hues selected for the color ramp is arbitrary; in this case the range of hues was selected for overall visual appearance and arranged by depth. By using a greater range of hues in the color ramp that are more closely keyed to bathymetric variations, it should be possible to increase the number of classes in an unsupervised isocluster autoclassification.

Interactive Supervised Autoclassification Methodology

It was expected to see increased efficiency when applying the interactive supervised autoclassification method across the color ramped LADS DEM, as shown in Figures 11 and 12. This is because a cognitive element is introduced to supplement the autoclassification algorithm. That cognitive element is presented in the form of analyst delineated training sites, which enclose specific spectral signatures to teach the autoclassification software how to interpret the remaining pixels in the image. This greatly differs from the unsupervised isocluster autoclassification because the analysis is no longer solely reliant on the undefined distribution of pixel values within the color ramped LADS DEM. Instead, individual geomorphological units are taught to the machine by associating very specific pixels hues in the form of training sites. However, the same limitation of the visual properties in the color ramped LADS DEM that was seen with the unsupervised isocluster autoclassification still persists when applying the interactive supervised autoclassification methodology. For example, because the range of hues in the LADS DEM color ramp shows minimal contrast throughout the image, certain geomorphological units are not easily delineated from one another; even...
Advantages and Disadvantages of Cognitive versus Autoclassification Methods

Cognitive mapping is an age-old tried and true method of approximating spatial distribution patterns on the ground. These efforts were severely limited in the marine environment, and it was not until the advent of remote sensing techniques during World War II that it was possible to conduct regional submarine mapping. Seismic methods, single beam sonar, sidescan sonar, and multibeam sonar techniques provided great advances in the recognition of submarine landscapes, but it was not until the arrival of LIDAR in the 1960s that it was possible to acquire digital bathymetric data at sufficient resolution to recognize discrete submarine landforms on continental shelves. With the ability to create colorized DEMs from LADS digital bathymetric data, it becomes possible to visualize seafloor features as never before seen. The cognitive maps derived from LADS bathymetry provide an interpreted picture of seafloor geomorphology, necessarily generalized to a level that is dictated by the hand-drawing agility of the cartographer. Because these kinds of maps are hand-drawn and based on visual interpretation, it does not make them any more or less useful than other kinds of maps. Simply put, the quality of the cognitive maps depends on the skill of the interpretation from the cartographer. It thus stands to reason that the more experienced and qualified the mapper, the more accurate the results. In fact, those without proper qualification and experience will find it impossible to produce useful products. A common “solution” in such cases is for researchers to turn to automated classifications expecting that an algorithm will solve the problem. The overarching problem here is that an automated classification will produce a map that differentiates the seafloor into different units or classes based solely on pixel arrangement. The key is to know what those units actually represent and where in the seascape they are correctly represented. Those units, however, can only be properly interpreted by those with appropriate training and experience in geomorphology. This oversight, a major pitfall that is associated with many automated classifications, may thus limit the usefulness of autoclassed maps of seafloor geomorphological features.

On the other hand, supervised machine classifications can be very useful and informative, as described by Erdey-Heydorn (2008) and Rozenstein and Karnieli (2011), for example. As in the analogy of a painting, much critical time and effort is required to prepare the canvas compared with the time spent actually painting. The same is true for the interactive supervised autoclassification, as careful consideration must
be given to the selection of training sites. Although training sites can be selected to represent different kinds of variability in the survey area, they are perhaps more valuable if selected to better define known geomorphological features. Such a procedure requires a priori knowledge of the seafloor, which can be obtained from cognitive observation and mapping.

It thus seems that both techniques, cognitive mapping and autoclassification, can be used to advantage in concert with one another. Each complements the other to help produce a more accurate, comprehensive product. That is, a cognitive mapping product refined by an interactive supervised autoclassification that further details the intricacies of seafloor spatial distribution patterns in the form of LADS bathymetry. The cognitive map provides a comparative control or reference for the interactive supervised autoclassification. Both products are useful in their own regard but acquire greater usefulness when blended into a composite.

**Future Mapping Techniques**

Both processes, supervised autoclassification and cognition, have their own sets of constraints that limit approximations of reality in the form of the kinds of maps that are produced in GIS (see for example Benedet and Finkl, 2003; Greene et al., 2005). Each approach has value or merit, and it would seem to behoove researchers to avail themselves of the composite approach that melds the two disparate methodologies. Further studies are required to know exactly how these methods can be best meshed together to produce a map that is more understandable than the experimental version shown in Figure 13, which serves only as a preliminary sample of what can be done. The merger of these two differently constructed map products could be the object of future research that will focus on the depiction of seafloor geomorphological units that in turn can be related to marine environments. The classification of benthic marine environments to a large degree depends on the geomorphological framework (e.g., Harris and Baker, 2011; Herzfeld and Higginson, 1996; Lundblad et al., 2006), which needs to be elucidated in the first instance.

**CONCLUSION**

Cognitive interpretation of digital LADS bathymetry enabled the production of maps showing seafloor geomorphological features on the continental shelf off the Florida southeast Atlantic coast. The original survey area covered about 600 km$^2$ and extended from the shore beyond the shelf break to the upper continental slope (Finkl and Andrews 2008, 2009; Finkl and Banks 2010; and Finkl, Benedet, and Andrews 2004, 2005a,b; Finkl et al. 2008). The small subset investigated here, covering an area of about 20 km$^2$, was used to investigate the possibility of machine classifying bathymetric data to ascertain what types of units would be possible to discriminate. Initial results of both the unsupervised isocluster and interactive supervised autoclassifications were promising because they broadly approximated geomorphological units that were cognitively identified and mapped. Upon further analysis, the
interactive supervised autoclassification with expert derived training sites provided the most discriminate map when compared with cognitive interpretations. Because of this general correspondence, it was possible to attempt not only correlation of maps produced by different methods but their merger into a new or different type of product. By overlaying the results of interactive supervised autoclassifications on top of the cognitively derived units, there appears the possibility of merging the two interpretations into a composite that highlights the advantages of both methodologies. ArcGIS contains the appropriate type of tool kit extensions for applying a montage process in the production of a computer refined cognitively derived map.

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Figure 13. A montage constructed by digitally overlying the interactive supervised autoclassification on top of the cognitive (manually interpreted) map of shelf geomorphology. Note the increased resolution provided in the overlaid autoclassification showing better discrimination of offshore sandflats on top of hard-bottom (pink areas), diabathic channel fields (black colored areas), coral reef subcrop (orange colored areas), and reef gaps (light green colored areas). Additional light green areas for reef gaps are, however, confused with several other morphological units.


