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Coastal Seafloor Geomorphological Features, Classification

Charles W. Finkl[1] and Christopher Makowski[2]
[1]Coastal Education and Research Foundation, Asheville, NC, USA
[2]Coastal Education and Research Foundation, Coconut Creek, FL, USA

Synonyms

Bathymetry; Coastal cartography; Coastal classification; Coastal geomorphological maps; Nearshore classification; Seafloor mapping; Seafloor topography

Definition

Coastal seafloor classification is based on the recognition of submarine features depicted by bathymetric patterns that are interpreted in terms of topography of marine origin or the identification of drowned terrestrial landforms. Coastal seafloor geomorphological maps are usually the products of interpretation, visually displaying digital bathymetric patterns through either cognitive reasoning or the result of computerized autoclassification algorithms. There are advantages and disadvantages associated with each approach (computerized autoclassifications versus cognitive interpretations), and the choice of procedure depends on purpose. Both methods are beneficial classificatory approaches, as they complement each other when interpreting coastal seafloor geomorphological features.

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., Finkl and DaPrato 1993; Mumby et al. 1998; Greene et al. 1999; Finkl 2004a, b; Mayer 2006; Collins et al. 2007; Chust et al. 2008; Walker et al. 2008; Achatz et al. 2009; Brock and Purkis 2009; Finkl and Vollmer 2011; Pittman et al. 2013; Makowski 2014; Finkl and Makowski 2015; Makowski et al. 2015, 2016, 2017; Makowski and Finkl 2016). The exemplar of the southeast Florida continental shelf has been studied using remote sensing techniques since the 1960s. The basic framework of these specific shelf features were outlined for the first time in reconnaissance seismic reflection profile surveys conducted by Duane and Meisburger (1969). Spatial distributions of shore-parallel coral reef tracts, inter-reefal sediment-filled troughs, and outcrops of carbonate bedrock were identified in their seismic reflection profiles. Subsequent LIDAR (light detection and ranging) surveys (2001 and 2008) in the form of LADS (Laser Airborne Depth Sounding) produced remarkably detailed depictions of shelf bathymetry. This kind of digital data is amenable to color ramping where tonal variations can be keyed to depth. Combinations of texture, tone, and pattern in the digital data provide a basis for cognitive (manual) interpretation of seafloor features. Maps showing spatial distribution patterns of seafloor features, for example, those prepared by Finkl et al. (2005a, b, 2007), Finkl and Andrews (2008, 2009), Finkl and Vollmer (2011), Steimle and Finkl (2011), Finkl and Makowski (2015), Makowski et al. (2015), Vollmer et al. (2015), Makowski et al. (2016), Finkl and Vollmer (2017), and Makowski et al. (2017) all recognize a range of marine landforms and drowned subaerial forms.

Cognitively derived (i.e., manually interpreted) maps are normally composed by hand and based on visual inspection, after which the mapping units are transferred into some sort of georeferencing informational software (e.g., ArcGIS). Finkl and Makowksi (2015) have shown that it is possible to classify bathymetric patterns using automated computer algorithms, such as unsupervised isoclustering and interactive supervised autoclassifications, which were then compared with previously prepared cognitive maps of field-verified seafloor features.

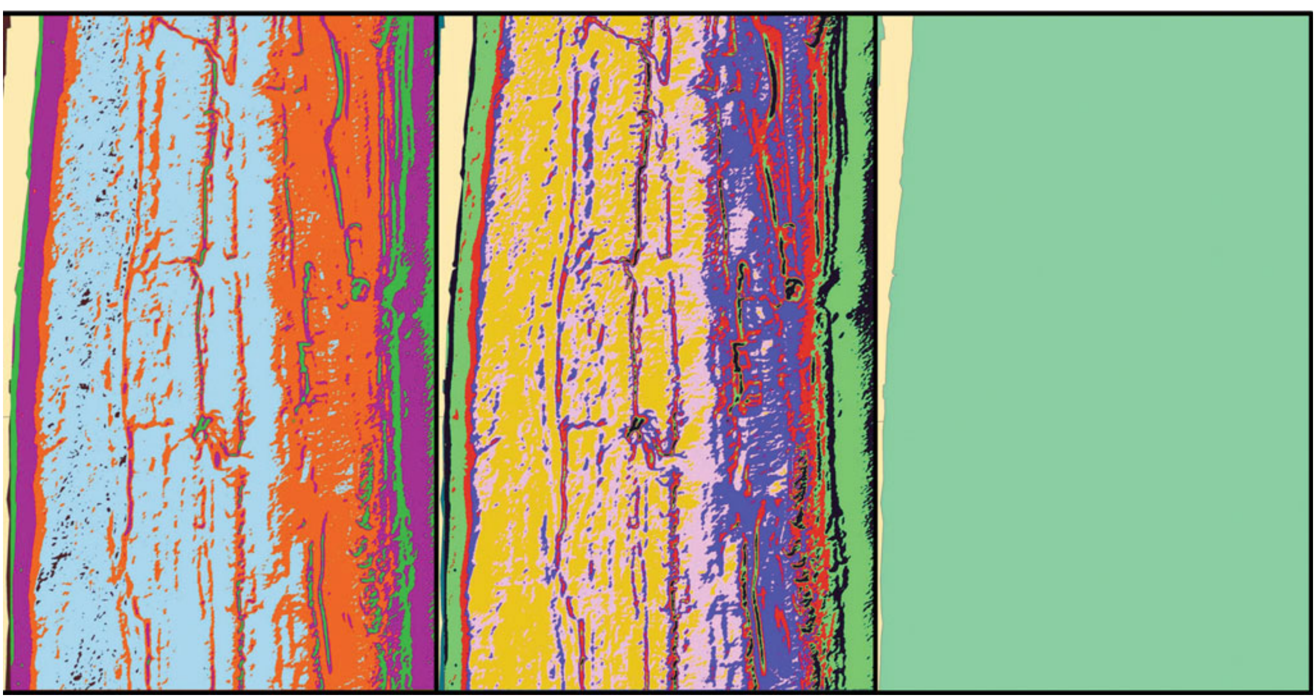
A good example of this involves the digital format of LADS (LiDAR) data, which makes the autoclassification of seafloor bathymetry possible. The basic procedure is to select a subset of the overall digital bathymetric dataset and compare the previously cognitive-identified geomorphological features (as described by Finkl et al. 2004, 2005a, b, 2008; Finkl and Andrews 2008, 2009; Finkl and Banks 2010) to auto-generated classifications of the same area. In order to determine whether autoclassification algorithms produce results comparable to cognitively interpreting, it is advisable to conduct a series of autoclassifying tests in appropriate geographical information system (GIS) software (e.g., ESRI's ArcGIS ArcMap).

In the example of the study area on the continental shelf off southeast Florida, the computerized classification of LADS digital bathymetry was divided into two parts, unsupervised isocluster and interactive supervised methodologies. Iterations of both methods were used to discern comparability with known seafloor geomorphological distribution patterns. Pixel digital numbers (DNs) were based on variations in color derived from color ramps that were applied to the DEM. Critical to this procedure is the number of classes that are discriminated by computer runs. Experimentation shows that a large number of autoclasses produces patterns that generally are not comparable with previously cognitive-derived geomorphological maps (Finkl and Makowski 2014; Finkl and Makowski 2015). Iterations using a dozen or so classes produce recognizable patterns in interactive supervised classifications, whereas unsupervised isocluster autoclassifications require ten or fewer classes. Details of the autoclassification procedures are briefly summarized as follows.

C

Unsupervised Isocluster Autoclassification Method

Within ArcMap, the Image Classification toolbar needs to be activated and an unsupervised isocluster autoclassification performed on a subset of the study area. After the appropriate input raster (composite of the RGB bands) is selected and the output-classified raster is renamed in the proper geodatabase, the number of classes is assigned using the same number of features interpreted from cognitive processes. In the LADS subset, for example, where 14 geomorphological features were cognitively interpreted, the number of untrained classes assigned for the unsupervised isocluster autoclassification was 14. Because untrained class counts greater than 10 for unsupervised isocluster analysis of the LADS bathymetry tends to produce unusable results (cf. Fig. 1), additional

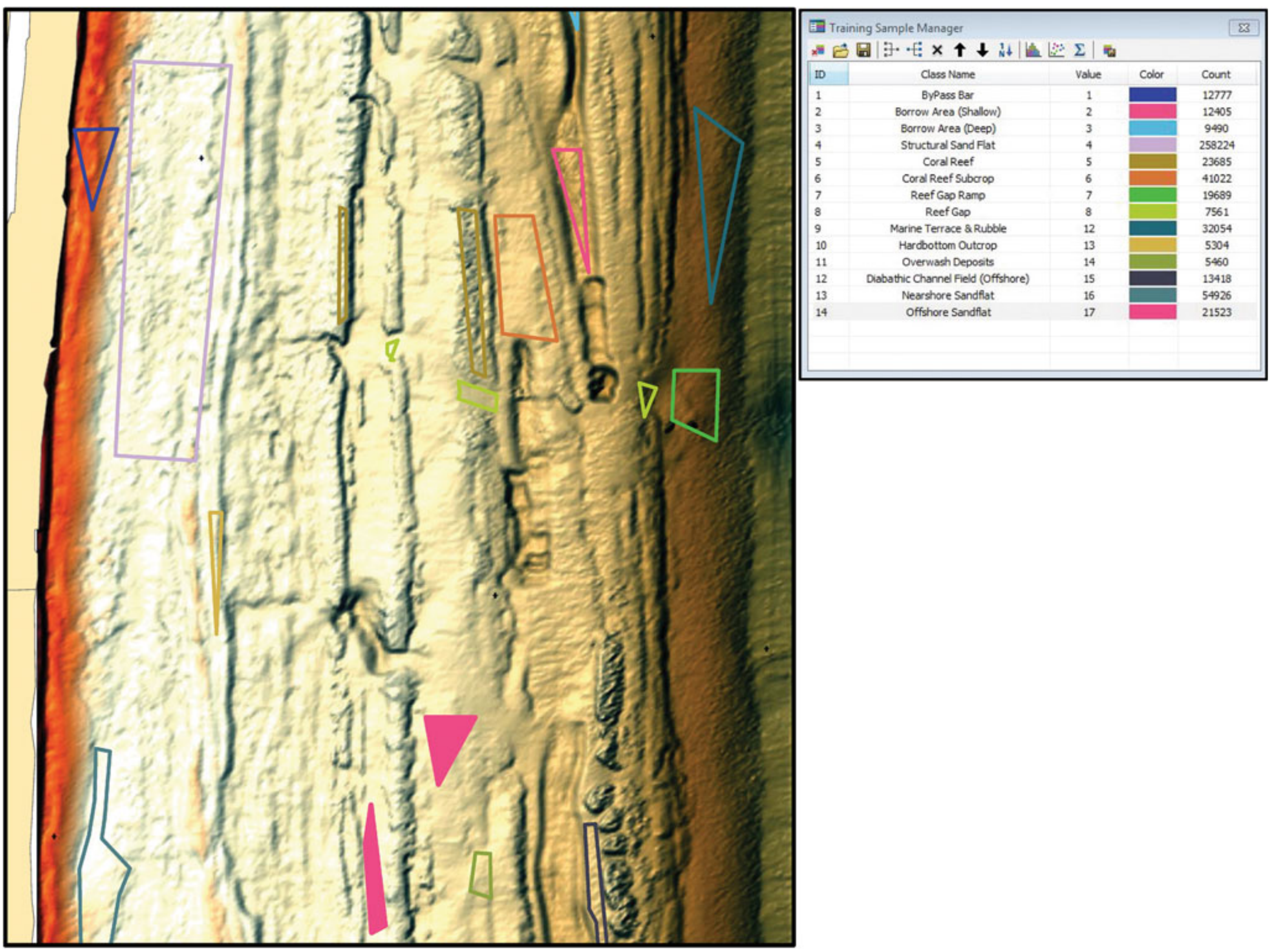


Coastal Seafloor Geomorphological Features, Classification, Fig. 1 Uninterpreted spatial distribution patterns derived from unsupervised isocluster analysis of LADS bathymetry DEM using five classes (left panel), seven classes (middle panel), and 14 classes (right panel). The larger number of classes in the third panel shows that increasing the number of classes does not necessarily improve discrimination of the imagery because, even though the same gross patterns are evident, the increased number of classes requires additional field verification. (Source: Finkl and Makowski 2015) unsupervised isocluster classification analyses were performed with five and seven untrained classes, after which individual output rasters were saved as Tiff image files and imported as layers into ArcMap adjacent to the raw images. These displays can then be exported and visually compared with cognitively interpreted displays of the same imagery to visually determine the degree of correlation of autoclassification.

Interactive Supervised Autoclassification Method

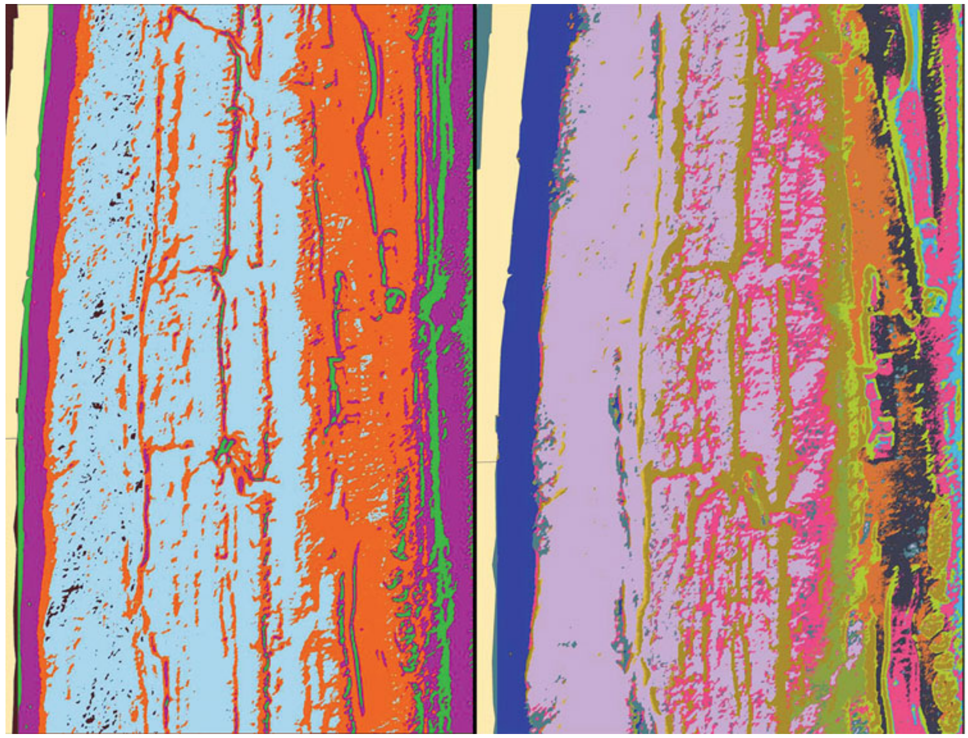
Within ArcMap, the Image Classification toolbar is activated, and an interactive supervised autoclassification performed on the same subset as the unsupervised isocluster method. Once an individual scene is selected in the drop-down window from the Classification toolbar, the Training Sample Manager window is opened. Training sites can then established for the interactive supervised classification that corresponds to pixel patterns used previously for cognitive interpretation of the seafloor features. For example, in the LADS digital dataset where 14 geomorphological features were cognitively interpreted, 14 training sites were established for the interactive supervised classification to match the visual cognitive criteria. The training fields shown in Fig. 2 contain variable shapes that are determined by geomorphological landform patterns. Selection of training fields is critical because they have to represent the feature or pattern that is autoclassified. The operator must therefore accurately train the program to recognize specified features or patterns.

After the interactive supervised classifications are performed, individual output rasters can be saved as Tiff



ID	Class Name	Value	Color	Count
1	ByPass Bar	1		12777
2	Borrow Area (Shallow)	2		12405
3	Borrow Area (Deep)	3		9490
4	Structural Sand Flat	4		258224
5	Coral Reef	5		23685
6	Coral Reef Subcrop	6		41022
7	Reef Gap Ramp	7		19689
8	Reef Gap	8		7561
9	Marine Terrace & Rubble	12		32054
10	Hardbottom Outcrop	13		5304
11	Overwash Deposits	14		5460
12	Diabathic Channel Field (Offshore)	15		13418
13	Nearshore Sandflat	16		54926
14	Offshore Sandflat	17		21523

Coastal Seafloor Geomorphological Features, Classification, Fig. 2 Locations of training fields used for the interactive supervised autoclassification of uninterpreted LADS digital bathymetry. Training sites represent the main landform features on the continental shelf, as determined from cognitive interpretation of texture, tone, and pattern observed in the color ramped DEM, which was then interpreted in terms of field-verified geomorphological features. The training sample manager legend shows matched pairings of landform class names with a training field color. (Source: Finkl and Makowski 2015)



Coastal Seafloor Geomorphological Features, Classification, Fig. 3 Cartographic examples of methodologies based on unsupervised isocluster analysis with five classes (left panel) and interactive supervised autoclassification with 14 classes (right panel). Both examples show organization of bathymetric patterns that variably correspond to cognitively interpreted landform units on the seafloor. Generalization and increased discretization is evident in both examples, as the number of classes required is dependent upon the purpose of the classification and the amount of detail needed. (Source: Finkl and Makowski 2015)

image files and imported as layers into ArcMap adjacent to the raw LADS images. These displays are then exported and visually compared with the cognitively interpreted maps to visually estimate the degree of correspondence with the autoclassification. Results of autoclassifying bathymetric data are shown in Fig. 3 where the left panel contains unsupervised isocluster classification using seven untrained classes and the right panel shows spatial distribution patterns derived from an interactive supervised classification using 14 trained classes.

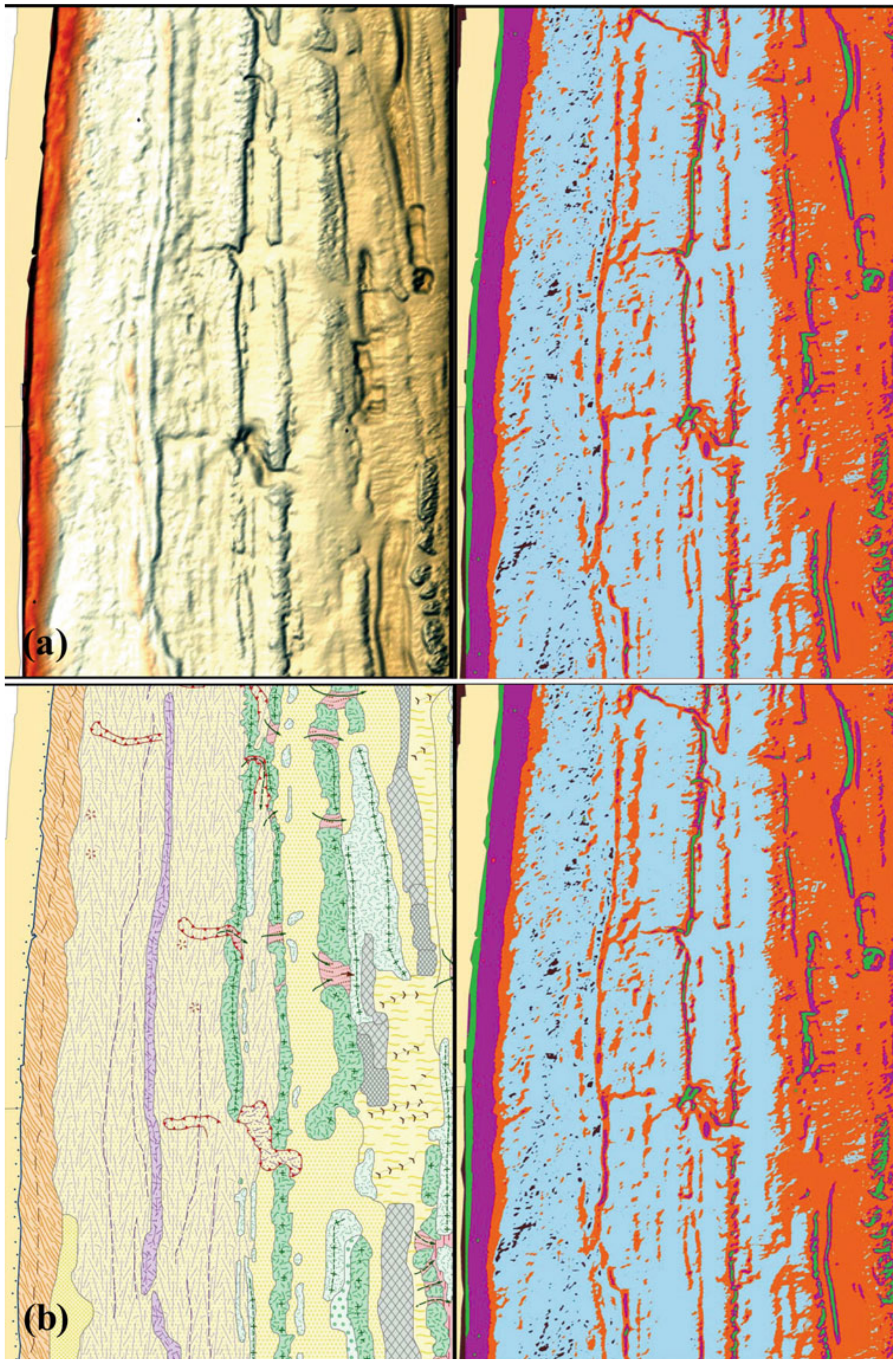
Comparing Classification Results

Visual comparison of the autoclassification results with a control shows a gross correspondence between the unsupervised isocluster autoclassification and the control. Detailed comparisons can, however, get complicated along the shore where three units are differentiated for the single larger bar and trough units on the LADS imagery (Fig. 4a). Bathymetric texture, tone, and pattern attributes are detected in the unsupervised isocluster classification, suggesting a basis for discerning discrete landform units. Ground truthing is required to verify units in the unsupervised isocluster autoclassification, but in situ familiarity with ground conditions suggest the following features: a surf zone unit close to the shore, crenulated bars alongshore, and fans or sediment splays seaward (Fig. 4b).

On the other hand, the interactive supervised autoclassification shows more complex spatial distribution patterns that correspond to parts of the cognitive map, as shown in Fig. 5. This map may seem confusing because it is a montage of two different approaches for depicting seafloor geomorphology. Careful study, compared to a cursory glance, shows many important interrelationships. Starting at the shore and moving seaward, for example, 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.

Classification Determination and Validity

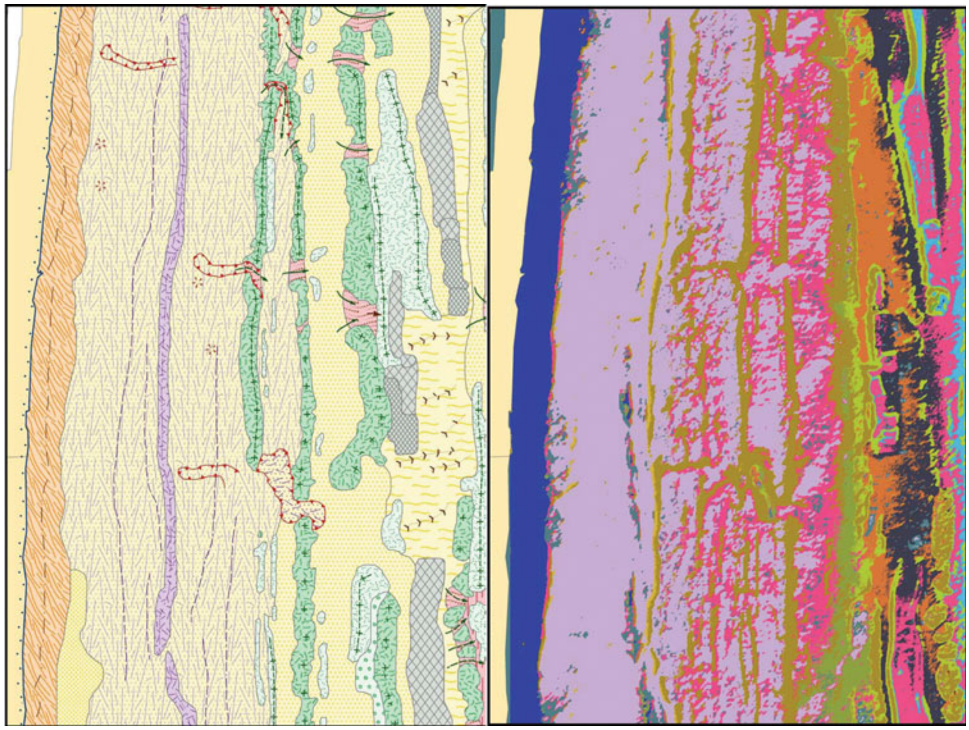
Before modern computerized mapping and GIS software packages, maps were validated in the field and compared with other maps known to be accurate. Although validation and accuracy assessments of computer-aided maps are usually achieved by statistical procedures and mathematical evaluation of self-tests, the visual comparison of machine-classified maps versus cognitively derived maps is simply a measure of correspondence. The advantage of these modern procedures lies in the pros and cons of an unsupervised isocluster autoclassification methodology and an interactive supervised autoclassification methodology when compared with mapping units based on the ratiocinative powers of the human brain. This process shows the possibility of producing composite maps of digital bathymetry.



Coastal Seafloor Geomorphological Features, Classification, Fig. 4 Comparison of unsupervised isocluster analysis (right panels) with unclassified (**a**) and classified (**b**) ramped LADS DEM. (**a**) Five-class unsupervised isocluster analysis (right panel) compared with (uninterpreted) color ramped bathymetry (left panel) showing the general correspondence of shore zone bar and trough features, coral reef tracts, bedrock outcrops, and dredge pits for beach renourishment projects. Symbolization of the geomorphological seafloor features is given in the legend to Fig. 6. (**b**) The same five-class unsupervised isocluster analysis (right panel) compared with cognitively interpreted geomorphic features on the shelf (left panel). These figures show generalization that occurs in maps hand-drawn at a nominal scale of 1:600 compared with greater detail that is acquired in autoclassification. (Source: Finkl and Makowski 2015)

Rationale for Classificatory Design

Digital bathymetric data provide new opportunities to investigate the nature of seafloor topologies. Digital data provide a dense sampling medium that can be manipulated to form a DEM of seafloor bathymetry. Elevations can be exaggerated to emphasize topographic differences that assist cognitive interpretation processes. A color ramp keyed to bathymetry can be draped over DEMs with an assumed light source to produce shadows. This colored representation of seafloor topography lends itself to visual inspection and consequent interpretation of



Coastal Seafloor Geomorphological Features, Classification, Fig. 5 Interactive supervised autoclassification (right panel) compared with cognitively interpreted geomorphic features on the continental shelf (left panel; a field-verified, color ramped DEM). This comparison shows the benefits of an interactive supervised autoclassification, which enhances the results of cognitive mapping seafloor features on the continental shelf. Cartographic generalizations in the cognitive maps are refined in supervised autoclassifications where the number of classes can be varied depending on special purpose investigations. (Source: Finkl and Makowski 2015)

bathymorphological features. This kind of observation and interpretation was not possible prior to the advent of digital surveys. The sample density of the LADS surveys (4-m resolution) was sufficiently detailed enough to allow construction of maps that allow interpretation of mesoscale geomorphological features (e.g., Finkl et al. 2004, 2005a, b, 2008; Finkl and Andrews 2008, 2009; Finkl and Banks 2010). This procedure is a major advance in the study of clear-water continental shelves and permits researchers comprehensive views of seafloor topologies.

Not all digital bathymetric data are amenable to automated classifications of the type applied to digital aerial and satellite images. In the case of hyperspectral data, for example, unsupervised classifications are more or less inept for interpretation of seafloor features. There are many reasons why hyperspectral data, usually measured with hundreds of narrow spectral bands about 10 nm apart, have prohibitive use for classificatory purposes. For example, in order to accurately obtain spectral signatures from hyperspectral data for different entities, such as different phytoplankton classes, zooxanthellae clades, or scleractinian (i.e., hard coral) species, it is necessary to first provide in situ spectral information. Without this information, the imagery cannot be interpreted because a function of the natural spectral variability is unknown. One such effort took place at Buck Island, St. Croix, U. S. Virgin Islands, where hyperspectral data obtained by AVRIS (air-borne visible infrared imaging spectrometer) was used in response to a mass coral bleaching event in the Caribbean. Kruse (2003) used the visible spectrum of AVIRIS light data reflecting off 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. Underwater handheld spectroradiometers first had to be used to measure reflected light readings from bleached coral so the hyperspectral imagery data could be calibrated to the in situ reflectance readings for an accurate interpretation. The procedure also requires that special geometric and atmospheric correction techniques are used to recalculate hyperspectral image pixels with data values that correspond to reflectance from the precise locations of those pixels. 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 condition is a function of fewer available photons in the narrow hyperspectral bands to interact with a sensor's detector elements. The consequence of this condition is very little image resolution to aid in the visual interpretation of the coastal environment. Lee and Carder (2005) recognized that a more cost-effective multispectral sensor is preferred over hyperspectral imagery when evaluating the major properties of coastal or shallow-water environments. Because digital bathymetry does not retain these disadvantages, there is an opportunity to investigate the possibilities of autoclassification procedures.

Unsupervised Isocluster Autoclassification Benefits and Limitations

The efficiency of unsupervised pixel clustering depends on the visual properties of the image being classified. Color ramped bathymetric DEMs generally do not offer a specific enough delineation of spectral signatures across the image. That is, 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 specific seafloor landforms. Because the color ramped 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 DEM, the same representative color is applied universally.

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

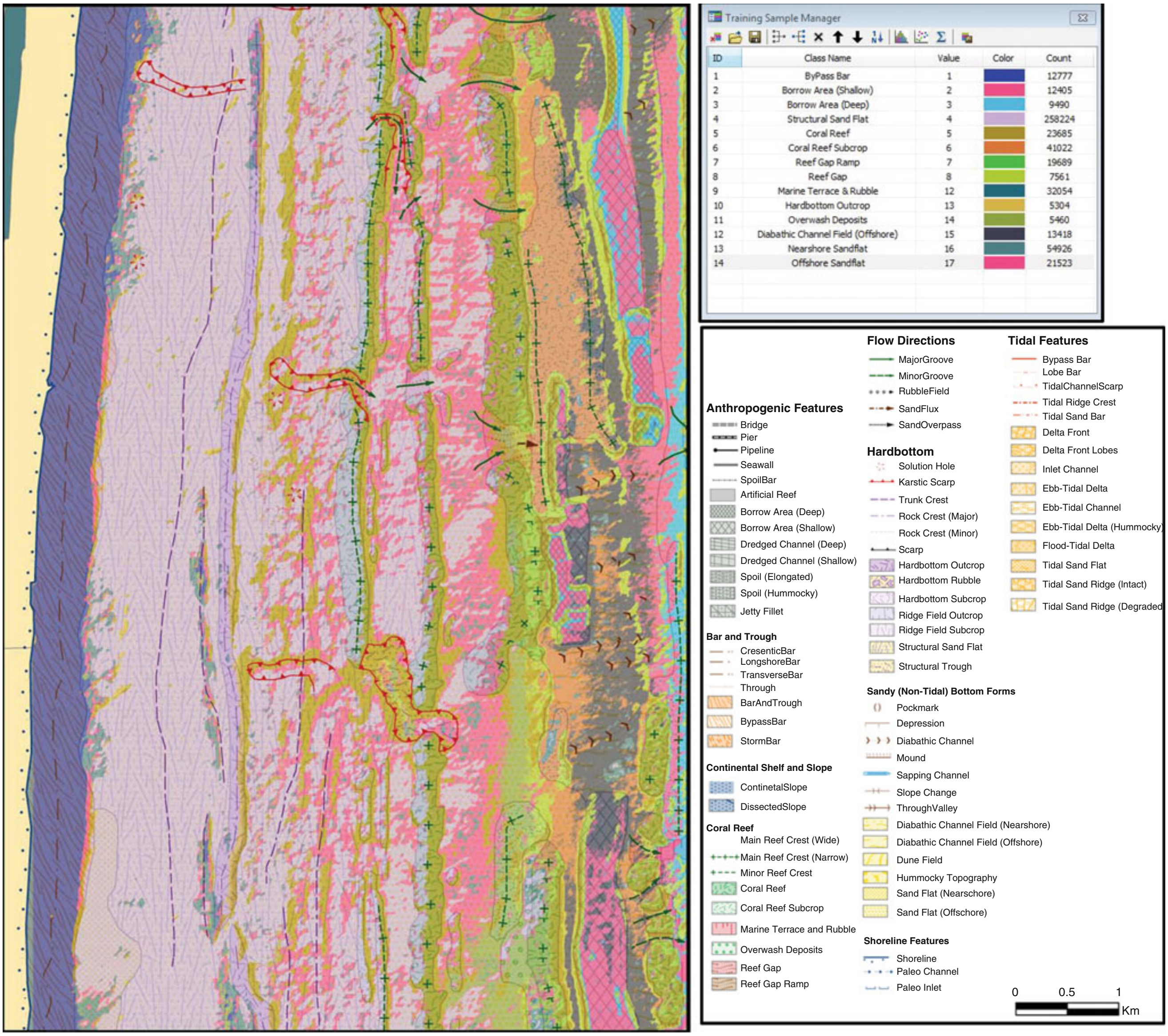
Interactive Supervised Autoclassification Benefits and Limitations

Increased efficiency can be expected when applying the interactive supervised autoclassification method across the color ramped DEM. 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 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 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 DEM color ramp shows minimal contrast throughout the image, certain geomorphological units are not easily delineated from one another, even with the provided training sites to guide the autoclassification process. Regardless of this limitation, the interactive supervised autoclassification provides efficiency in the number of seafloor unit boundaries that could never be achieved with cognitive, hand-drawn cartography.

Cognitive Versus Autoclassification Methods

Cognitive mapping is an historical 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 submarinescapes, 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 digital bathymetric data, it becomes possible to visualize seafloor features as never before seen. The cognitive maps derived from digital 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. The quality of the cognitive maps depends on the skill of the interpretation from the cartographer. That is to say, the more experienced and qualified the mapper, the more accurate the results. Because researchers without proper qualification and experience find it impossible to produce useful products, a common "solution" is to turn to automated classifications. Unfortunately, a new problem arises because an automated classification produces 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, limits 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). 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



Coastal Seafloor Geomorphological Features, Classification, Fig. 6 This montage was created by digitally overlying an interactive supervised autoclassification on top of a cognitive (manually interpreted) map of shelf geomorphology based on digital bathymetry in a LADS format. Increased resolution is provided in the overlaid autoclassification which gives better discrimination (more details) of offshore sandflats on top of hard-bottom (pink areas), diabathic channel fields (gray colored areas), coral reef subcrop (orange colored areas), and coral reefs and reef gaps (light green colored areas). Somewhat problematic are some light green areas for reef gaps that may be confused with several other morphological units, such as coral reefs, coral reef subcrop, and overwash deposits. (Source: Finkl and Makowski 2015)

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.

Both techniques in question, cognitive mapping and autoclassification, can be shown with great advantage when used 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 a software-driven autoclassification algorithm, further details the intricacies of seafloor spatial distribution patterns in the form of digital 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 or montage (Fig. 6).

Both processes, autoclassification and cognitive mapping, 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; Finkl and Makowski 2015). Each approach has value or merit, and greater insight into seafloor features can be achieved by applying the composite approach that melds the two disparate methodologies.

Conclusion

Classification of coastal seafloor geomorphological features can be achieved either through a cognitively derived interpretation or an autoclassificatory algorithm run by geospatial software. The interactive supervised autoclassification with expert-derived training sites provides the most discriminative map when compared with cognitive interpretations. Because of this general correspondence, it is possible to overlay the results of interactive supervised autoclassifications on top of cognitively derived units, thereby merging the two interpretations into a composite that highlights the advantages of both methodologies. Modern georeferenced software packages, such as ArcGIS, contain the appropriate type of tool kit extensions for applying a montage process in the production of a computer refined cognitively derived map. By applying both processes in tandem, a more efficient classification effort is achieved.

Cross-References

▶ Altimeter Surveys, Coastal Tides, and Shelf Circulation
▶ Beach and Nearshore Instrumentation
▶ Beach Profile
▶ Coastal Modeling
▶ Geodesy
▶ Geographical Coastal Zonality
▶ Holocene Coastal Geomorphology
▶ Nearshore Geomorphological Mapping
▶ Nearshore Sediment Transport Measurement
▶ Photogrammetry
▶ Remote Sensing of Coastal Environments
▶ Shoreline and Coastal Terrain Mapping

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Coastal Sedimentary Facies

H. Edward Clifton
US Geological Survey, Menlo Park, CA, USA

Introduction

Coastal sedimentary environments include a variety of physical and biological processes, which act on coastal sediment to produce associations of composition, texture, primary sedimentary structures, and fossils. These associations constitute sedimentary facies, lithologically distinct, genetically related components of a sedimentary system, or environmental facies, whereby a set of specific environmental processes imparts a distinctive character to a sediment. Coastal sedimentary facies provide the signature of specific types of coastal deposits and facilitate their identification in the geologic record.

This entry describes some of the more common clastic sedimentary facies associated with open coasts and coastal embayments. For a review of carbonate coastal facies, the reader is referred to Demicco and Hardie (1995). The discussion here also does not address facies of high-latitude coasts or low-latitude coasts dominated by mangrove swamps (see Hill et al. 1995; and Cobb and Cecil 1993, respectively). Many of the facies described here form in both marine and lacustrine settings, although tidally influenced facies are restricted to the marine environment.

For more detailed information on coastal sedimentary facies, the reader is referred to the excellent summaries provided by Reineck and Singh (1973), Davis Jr. (1985), Walker and James (1992), Galloway and Hobday (1996), and Reading (1996).

Coastal Sedimentary Processes

A complex array of processes influence coastal sedimentary facies (Fig. 1). Of these the most important are waves, tides, and biogenic processes. Sediment input is also critical to the facies character (grain size) and to the nature of the preserved deposit (sedimentation rate).

Waves may exist as "seas," driven by local winds, or as "swell," generated by distant storms. Swell tends to have longer period and to influence the seabed to greater depths

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