

COASTAL ZONE LANDSCAPE CLASSIFICATION USING REMOTE SENSING AND MODEL DEVELOPMENT*

Kevin R Slocum, US Army Topographic Engineering Center, USA
James E. Perry, Virginia Institute of Marine Science, USA

ABSTRACT

Coastal zone landscapes can be studied through the use of remote sensing and model development. Four related studies are summarized in this paper that address common issues and concerns faced by resource managers in the monitoring and characterization of landscape conditions within a coastal zone. The initial study examined variable spectral and spatial image resolutions and training sample methods required for the accurate classification of a coastal landscape. Imagery with 25nm bandwidth and 4m pixel size outperformed three other image resolution combinations, as determined by comparing the accuracy of image classification with field-based truth data. Thirteen natural and cultural landscape features were classified. The second study investigated the capability of high-resolution multi-spectral imagery to characterize *Phragmites australis* L. stands into high, medium and low categorical biomass classes. Ten *P. australis* sample sites were grouped into these three classes based on image reflectance values and field-based biomass measurements. Similarity of group members showed that reflectance values distinguished rank ordered differences in biomass between various *P. australis* stands. In the third study, correction of an imagery-derived cover classification map was accomplished by assignment of expert knowledge, integration of that of knowledge into a simple spatial model, and subsequent generation of a revised cover map. A partial prototype selection of expert rules was sufficient to change more than 20 percent of the originally classified landscape pixels entirely by post-classification. The final study discusses the development of an empirical model that used vegetation community classes to predict the characteristics: a) soil type, b) soil compaction rate, and c) elevation. Vegetation class distribution proved to be a reliable surrogate for estimating these variables based on field-based statistical scores of association and significance tests. Mapped estimates of soil type, soil compaction at 12 and 18inch depth, and elevation are provided to illustrate spatial variables estimated from vegetation types. The results of the four studies completed for this paper suggests various image resolutions and methods to acquire resource data that might be used in landscape level ecological modeling.

INTRODUCTION

The world's coastal zone is one of the most dynamic areas of the world, with 440,000 km length of shoreline where the processes of the land and sea are brought together (Cooke and Doornkamp, 1990; Krabill *et al.*, 2000). Coastal zones do not have well defined boundaries but are considered to be the terrestrial area landward of the land-sea interface that is influenced by the sea; specifically, it includes the zone of surf where waves influence the land, the dune zone, and the zone of vegetation influenced by salty groundwater, salt aerosols, and storms which all affect plant growth (Ahnert, 1996). Many issues affect coastal and marine resources, including: population increase (Cohen *et al.*, 1997), heavy metals (Knight and Pasternack, 2000), excess nutrient loadings, over-fishing, introduction of overheated water from factories, habitat loss, sedimentation, marine and beach debris, oil spills, sea level rise (White and Pickett, 1985; Nicholls *et al.*, 1994; Nicholls and Leatherman, 1995), coastal property rights, loss of biological diversity and non-indigenous species (Marsh and Dozier, 1981; Smith, 1996; French, 1997). Disturbances along the coast have a profound effect on plant and animal life (Huggett, 1995). The problems of coastal management do not recognize artificial political borders (Cooke and Doornkamp, 1990).

Strategies to protect coastal systems have proved difficult to implement (Turner and Schubel, 1994). Fortunately, technological advances do provide potential tools to assist in decision-making for long-term sustainability of our planet. These include: a) software models (Lam *et al.*, 1998 {environmental monitoring}; Quattrochi *et al.*, 2001 {thermal urban landscapes}; Sanders and Tabuchi, 2001 {flood risk assessments}; b)

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geographic information systems (Janssen *et al.*, 1990); and c) remote sensing (Harris and Ventura, 1995; Jensen, 1996; Cihlar *et al.*, 2000a; Steele, 2000). These technologies are available and ready for inclusion into a resource manager's tool-box. Resource managers should, however, closely consider present capabilities, and limitations, of these tools for deriving geospatial data needed to support GIS and ecological models (Wessman *et al.*, 1998).

Long-term studies of our varied environments and the monitoring of competing influences of nature and man are critical for decision-makers to have information enabling them to make informed judgments (Cooke and Doomkamp, 1990; Cihlar *et al.*, 2000b; Slater and Brown, 2000). The term landscape, as defined by Lyle (1999), is considered to be an ecosystem comprised of biotic and abiotic element interaction, flow of energy and materials, and land resource inventory. A land resource inventory is a necessary beginning for environmental planning or resource management decision-making (Lyle, 1999). Remote sensing provides a fast, accurate, affordable means to acquire such land resource data (Redfern and Williams, 1996). This land resource data is crucial to assist in determining the functioning of terrestrial ecosystems (Cihlar *et al.*, 2000b). Much of this needed data has yet to be acquired. For example, United States land resource data (specifically, Anderson level II data) is only about 60% complete for all land resource cover classes (Yang *et al.*, 2001; Vogelmann *et al.*, 2001). Additional data will need to be acquired to fill in the missing 40%, and updated data sets of the present 60% coverage will be routinely required from a growing user community expectation for current land cover data for monitoring purposes (Vogelmann, *et al.*, 2001).

The purpose of this collection of related studies was to show how coastal zone landscape can be characterized using remote sensing and empirical model development to the betterment of the resource management community. Four related remote sensing studies are summarized with results that can be applied by resource managers. The first study examined spectral and spatial resolution requirements for accurate landscape cover classification. Study two investigated the capability of imagery to remotely assess biomass differences in stands of *Phragmites australis*. This work extended the first study by continuing beyond class measurements only and into quantitative measurements of a specific plant community. The third study describes results of a post-classification technique designed to correct misclassifications in cover class maps derived from imagery. Expert knowledge was used to parameterize a spatial correction model of a barrier island environment. The final study discusses the development of empirical models that use vegetation community class to predict a) soil type, b) soil compaction rate, and c) elevation. In the absence of a direct remote sensing method for measuring soil conditions and elevation, or in other words, where the surface is concealed by vegetation, the vegetation itself was used a surrogate to indirectly estimate soil and elevation variables. Collectively, these studies address common issues and concerns a resource manager faces with the monitoring and characterization of landscape conditions within a coastal zone.

METHODS

The first study was an investigation at Fort Story, Virginia of spectral, spatial, and spectral and spatial resolution combined, as well as a review of six training sample methods used. Figure 2 shows a false color composite image of 1m spatial multispectral (MSI) imagery acquired in May 1999 over the Fort Story site using 25nm bandpass filters. The study site is approximately 400 x 500 meters in size representing a mixture of manmade and natural land cover classes that are typical of the entire installation. The classification accuracy of maps compiled from imagery with wide bandwidths (75nm) was compared to the accuracy of map classifications derived from narrow bandwidths (25nm).

Study two described a method for determining categorical measures of biomass *P. australis* from high-resolution multispectral imagery. The field site was the uninhabited Parramore Island barrier off the eastern shore of Virginia (see Figure 1). Eighteen barrier islands make up a chain trending northeast-to-southwest off of Virginia's Eastern Shore, with Parramore Island as the central-most island in this barrier chain. No permanent human population inhabits the island and activities such as agriculture, hunting, logging or similar activities are prohibited. *Phragmites australis* is an undesired opportunistic invader species that can quickly overtake native plant habitat (Figure 4). *Phragmites australis* needs to be monitored by resource managers because of its propensity to out-compete other native and threatened plant species (Marks *et al.*, 1994; Pyke *et al.*, 1999). Routine surveillance of *P. australis* will help ensure that lateral advancement is controlled. Multispectral imagery and coincident field data found in Table 1 (average plot stand height, stems per meter, and average culm diameter) were acquired and then normalized after conversion using a linear scale transform with maximum score procedure (Malczewski, 1999). "Plots" represent the sample plot; "height" is average stand height in meters; "stems" are number of stems in a sample plot; "culm" represents the average diameter of stems measured 15cm above ground; "under" represents the

understory percentage of herbaceous plants; “biomass class” represents a categorical classification of biomass value, where “biomass” values are computed from the equation: $H * S * C = B$, where, H = average plot stand height, S = stems per meter, C = plot culm diameter, and B = plot biomass.

The third study was the creation of a simple methodology for improving a land cover classification map of Parramore Island, VA. Cover classification maps defined from image processing often contain errors. It is not uncommon to find that some mistakes are plainly visible. Targeting these misclassifications can be difficult with the standard tools available within image processing software. In this study, ecological rules were introduced to strategically target and correct classification mistakes. A four-step process was implemented. First, ecological expert knowledge was acquired about the study site. This could be acquired from field expertise or literature sources. Second, misclassifications were visually identified based on the expert knowledge. Third, IF-THEN-ELSE conditional statements were loosely developed to address the mistakes. Lastly, conditional statements were implemented within ERDAS Imagine Spatial Modeler image processing code as a post-classification correction model. Conditional rules were converted into interpretable statements with ERDAS’ Majority Focus optional statements. All rules were spatial in nature, in that change was effected only by adjacency of feature class pixels identified by the model analyst. The analyst defined the criteria for selected pixels to change to a new, ecologically sound feature class. Six rule corrections were used to post-classify the Parramore Island cover class map that resulted in the conversion of over 20% (173 of the total 850 hectares) of the initial land cover classification pixels to alternative classes. The method of post-classification correction described in this section is portable in the sense that the rules can easily be changed and adopted to a new physiographic environment; the model template is extendable to new domains.

The last study at Parramore Island investigated field data relationships between vegetation community classes and: elevation, soil type and soil compaction strength, with intent to develop empirical prediction models. Vegetation class was selected as the dependent variable because these types of data are considered to be readily interpretable from remote sensing source (Jensen, 1996). Accordingly, if vegetation classifications were established remotely, and empirical relationships were established between vegetation, soil, and elevation field data, then vegetation class maps could be used to estimate the other variables. Strength of association non-parametric statistics were used to assess the inter-relationship between variables. Elevation heights were grouped into one of three categories. Soil type was divided into four classes and compared to vegetation community. Soil compaction strength scores were recorded at depths of 0, 5, 15, 30, and 46cm.

RESULTS and DISCUSSION

STUDY SITE 1

Based on the independent contribution of bandwidth alone, the narrower bandwidth imagery returned higher Kappa and overall accuracy scores, in addition to improvements in the transformed divergence scores for training samples that were difficult to spectrally separate into distinct classes. Specifically, 25nm imagery resulted in higher accuracy cultural feature classifications and a combination of natural and cultural features. In a similar test, the independent contribution of spatial resolution was tested to determine if imagery with 4-m pixels returned statistically equivalent image classifications to imagery with 1m pixels. Transformed divergence scores of difficult to separate training sample pairs improved with the 4m imagery. Kappa scores suggest that natural features are better interpreted from 4m imagery than 1m imagery. Classification accuracy of natural features from 4m imagery was consistently 5% better than accuracy achieved from 1m imagery. Classification from cultural, and natural and cultural, features were statistically similar regardless of pixel size.

The joint contribution of spectral and spatial resolution was evaluated. Accuracy results for the narrow bandwidth 25nm imagery with the larger 4m pixel size generally outperformed the other three image resolution combinations. The results were statistically different between 25nm/4m imagery and 70nm/1m imagery for a classification of both natural and cultural features, but were not statistically different between 25nm/4m and the remaining combinations. Figure 3 shows the combined contribution of spectral and spatial resolution as an overall accuracy of classification for natural and cultural features with training sample methods grouped into 25nm/1m, 25nm/4m, 70nm/1m, and 70nm/4m classes, and plotted from highest to lowest to score to illustrate differences. Independently, accuracy of classifications from 25nm bandwidth imagery was statistically better than 70nm imagery; likewise, accuracy of classifications from 4m pixel size imagery was statistically better than 1m imagery for natural features.

Six training sample methods were compared. An effective number of training sample pixels were acquired from both the seed grow 15- and 25 methods, as determined from the successful accuracy assessment scores of image classifications processed using these methods. These methods are a more replicable, objective training sample selection process. The polygon training sample method was also effective.

STUDY SITE 2

Biomass values were computed for each stand from normalized field data by a linear scale transform with maximum score procedure (Malczewski, 1999). *Phragmites australis* biomass and various combinations of image channel reflectance values were evaluated by clustering analysis tools. Classes and class members defined for biomass were closely matched to those of red-channel classes. Forward stepwise multiple regression was applied to selected image channel reflectance values to test for correlation to biomass class assignment. Four image channels (green, blue, red, NIR) were identified as contributing to 96% of the overall variance, with the red-channel explaining 79% of the variance; red and NIR explaining a cumulative 85% of the variance; red, NIR, and green explaining a cumulative 90% of the variance; red, NIR, green, and blue explaining 96% of the variance (Table 2).

STUDY SITE 3

In Figures 5 a to d, a sequence from original unclassified imagery, to classified imagery, to post-classified imagery, to a final difference map are displayed. Multispectral imagery has been acquired and processed into classified imagery to demonstrate the impact of integrating post-classification rules. Figure 5a is an original 4-channel multispectral imagery of Parramore Island, collected in May 1999 at an altitude of approximately 3,000 meters above MSL which resulted in a nominal pixel size of approximately 1.5 meters, shown in a false-color 4-3-2 band representation. Figure 5b is an initial supervised classification of land cover classes from the raw imagery, prior to the application of any rule-based classification to improve the results. Speckle and misclassifications are visually evident. Figure 5c shows the resulting map compilation after running the spatial model and making corrections to the original class map. Respective legends for Figures 5b and 5c identify the changes to class area in hectares. Spatial pattern was more reasonable with speckle and misclassified pixel areas removed in Figure 5c. Homogeneity typically found in vegetation complexes of the barrier island were evident in Figure 5c. Lastly, Figure 5d is the difference map between Figures 5b and 5c, depicting those pixels changed by the incorporation of the rules.

STUDY SITE 4

Maps depicting estimated elevation, soil type, and soil compaction are found in Figure 6. Figure 6a is the original multispectral 4-channel imagery, acquired in May 1999, displayed as a false color composite image of Parramore Island, Virginia. Figure 6b shows both the vegetation classes that were derived from the imagery using a supervised classification method, and soil compaction attribution estimated for each class at 30 and 46cm depths. These estimates were based on earlier ANOVA and Cramer's V tests indicating strength of association. Figure 6c is a soil type class map that was compiled by a simple recode of vegetation classes that had been grouped into three categories. Each vegetation class had a corresponding soil type that was mapped. Figure 6d is an elevation class map that was re-coded from vegetation classes that had been grouped into three categories.

A Cramer's V score of association between 3- vegetation classes and their respective elevation values resulted in a positive score of: 0.99, with a value of 1.00 representing perfect association between the variables. Map found at Figure 6d. Additionally, equations were developed from field transect to estimate dune height and crest location concealed by maritime forest. These ratios suggested consistency in dune shape, height, and crest location, with respect to overlying forest width. Vegetation community class was shown to have a strong positive association with four soil type classes. The Cramer's V score: 0.85, suggests that vegetation could be used to estimate soil type locations on Parramore Island. The soil type map of the island (Figure 6c) provides insight into the physical processes of sediment delivery and removal that have shaped it's geomorphology. Multivariate analysis of variance between vegetation and soil compaction strength resulted in highly significant p-values at all depths. Vegetation type explained the variance in soil compaction at deeper 30 and 46cm depths ($R^2 = 0.88$ and 0.72 , respectively). Cramer's V measures were computed for 10, 7, and 3-vegetation classes and soil compaction strength with scores of at least 0.85 for both 30 and 46cm depths. The greater variation in the soil compaction rates for 30 and 46cm depths was responsible for the increased Cramer's V strength of relationship scores with vegetation type. Greatest variation in rates was observed for upper marsh communities, while least variation was consistently evident from the lower marsh *S. alterniflora*. and *P. taeda* dune communities (ranges, be depth, found in Figure 6b).

SUMMARY and CONCLUSIONS

Image spectral and spatial resolution, in addition to training sample method, had a statistical effect on land cover classification accuracy. 25m/4m imagery achieved the best classification accuracies of the four images tested. Selection of image resolution should closely consider the intended cover classification mapping. One-meter imagery was capable of separating *P. australis* stands into high, moderate and low-density biomass, with equivalent classes and membership that were derived from normalized field data. This finding begs the question: are high-density stands the first to expand laterally, and if so, can remote sensing be useful for targeting high-density sites in need of immediate mitigation. Strategic mitigation of advancing *P. australis* would help resource managers protect higher-value plant communities and avert a potential decline in ecosystem health attributable to loss of plant diversity/complexity, loss of shelter/habitat, and decline in food source. Ecology-based rules that were applied to a cover classification map showed that significant changes could continue to be made in improving map accuracy. Classification rules that were user-assigned gave direct control to the image analyst in the correction process. Lastly, estimation of soil properties and sub-meter elevation from vegetation community surrogates offered an alternative resource inventory collection technique. Additionally, soil data was not collected and interpolated from point data, but rather as raster areal data.

In each of the four studies, multi-spectral imagery played an integral role in defining the cover condition of a coastal landscape. Remote sensing is an excellent tool to assist in the management of the coastal zone. Up-to-date imagery and landscape classes derived from it are essential tools to help resource managers make informed decisions. Remote sensing should be driven by scientific hypothesis and any future modeling should account for a remote sensing and landscape process model merge (Wessman *et al*, 1998). To date, implementation of remote sensing in landscape ecology research and applications has been relatively scarce (Gulinck *et al*, 2000). Ecological models should be designed to use direct or derived variables from remote sensing (Wessman *et al*, 1998). The results of the four studies completed for this paper suggests various image resolutions and methods to acquire resource data that might be used in landscape level ecological modeling.

The future of remote sensing is bright. Detailed, accurate measurements of the ocean, land, and atmosphere are planned by satellite sensors. Many camera systems are already orbiting earth including the MODIS (Moderate-Resolution Imaging Spectroradiometer) measuring biological and physical processes such as plankton, land vegetation, and clouds; MISR (Multi-angle Imaging Spectro-Radiometer), measuring atmospheric aerosols; ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer), providing 15m horizontal spatial resolution imagery for elevation and landform mapping, surface temperatures, and rock cover types, and MOPITT (Measurements of Pollution in the Troposphere) measuring methane and CO² (Glaze, 1999). LIDAR technology offers particular promise for the mapping of elevations at 15 to 100cm vertical accuracy in an accurate, timely, and economical way (Hill *et al*, 2001). Hyperspectral sensors are currently acquiring data by airborne and satellite platform and hold promise for better spectral separation of biotic features due to narrower bandwidths. Ecological monitoring from remote imagery will continue, as testified to by the \$30-million dollar annual remote sensing-based ecological monitoring and assessment program (EMAP), the National Science Foundation's continued investment in remote sensing for their Long Term Ecological Research (LTER) program, and the US Forest Service use of imagery for their forest health monitoring program (Stone, 1995).

Remote sensing offers a technological advantage to a resource manager. A simple way to determine if remote sensing is an appropriate tool for coastal zone landscape characterization is to overwhelmingly answer "yes" to the following questions.

- Are the desired landscape data useful for multiple projects?
- Is this, or should this site be a routinely monitored?
- Is this project too large to map on the ground with available resources?
- Is the project site largely inaccessible?
- Is this a project site best understood from a complete picture (imagery) rather than a sampling of field points?

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TABLES AND FIGURES

Table 1. Normalized Field Data.

Plots	Height	Stems	Culm	Under	Biomass	Biomass Class
phrag20	0.8	0.56	0.79	0	0.35	Moderate
phrag21	1.0	0.59	0.92	0	0.55	High
phrag22	1.0	0.79	1.00	0	0.79	High
phrag23	0.8	0.40	0.63	0	0.20	Moderate
phrag24	0.6	0.14	0.41	0.55	0.03	Low
phrag25	0.6	0.60	0.75	0	0.27	Moderate
phrag26	0.6	1	0.62	0	0.37	Moderate
phrag27	0.4	0.051	0.53	0.7	0.01	Low
phrag28	0.6	0.63	0.55	0.5	0.21	Moderate
phrag29	0.8	0.93	0.54	0	0.40	Moderate

Table 2. Summary of Stepwise Multiple Regression for Image Channel Reflectance Values

Image Channel	+in/-out	Pearson's R	R ²	R ² change	p-level
Red	1	0.89	0.79	0.79	0.00
NIR	2	0.92	0.85	0.07	0.12
Green	3	0.95	0.90	0.05	0.12
Blue	4	0.98	0.96	0.06	0.05
NDVI	5	0.99	0.97	0.01	0.30

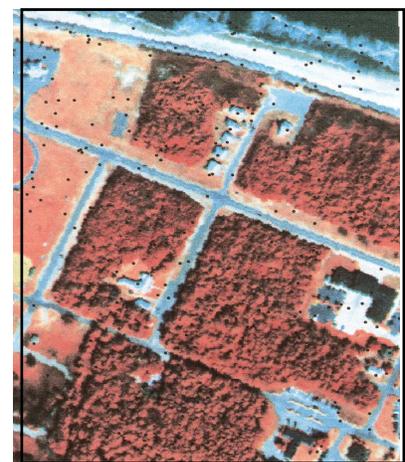
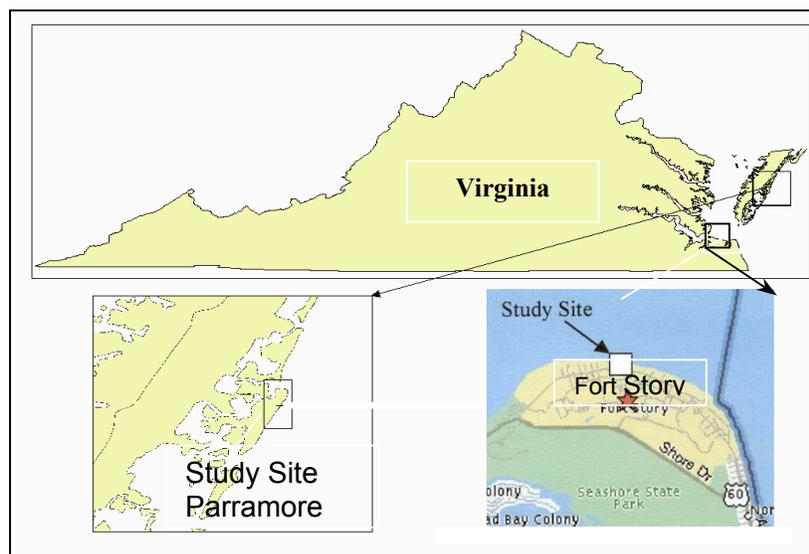


Figure 1. Study Sites: Fort Story and Parramore Island, Virginia, USA.

Figure 2. False color MSI Imagery.

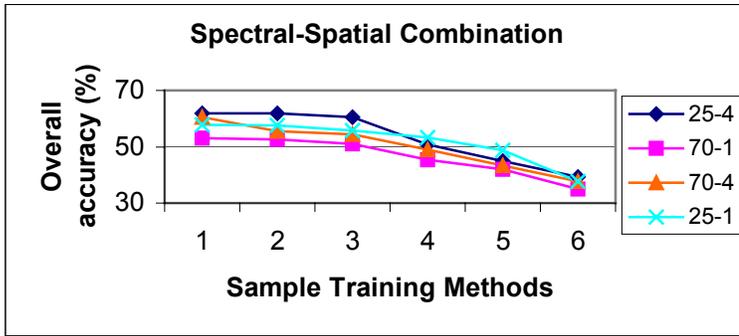


Figure 3. Spectral-Spatial Image Resolution Accuracy



Figure 4. Invasive *P. australis* Stand.

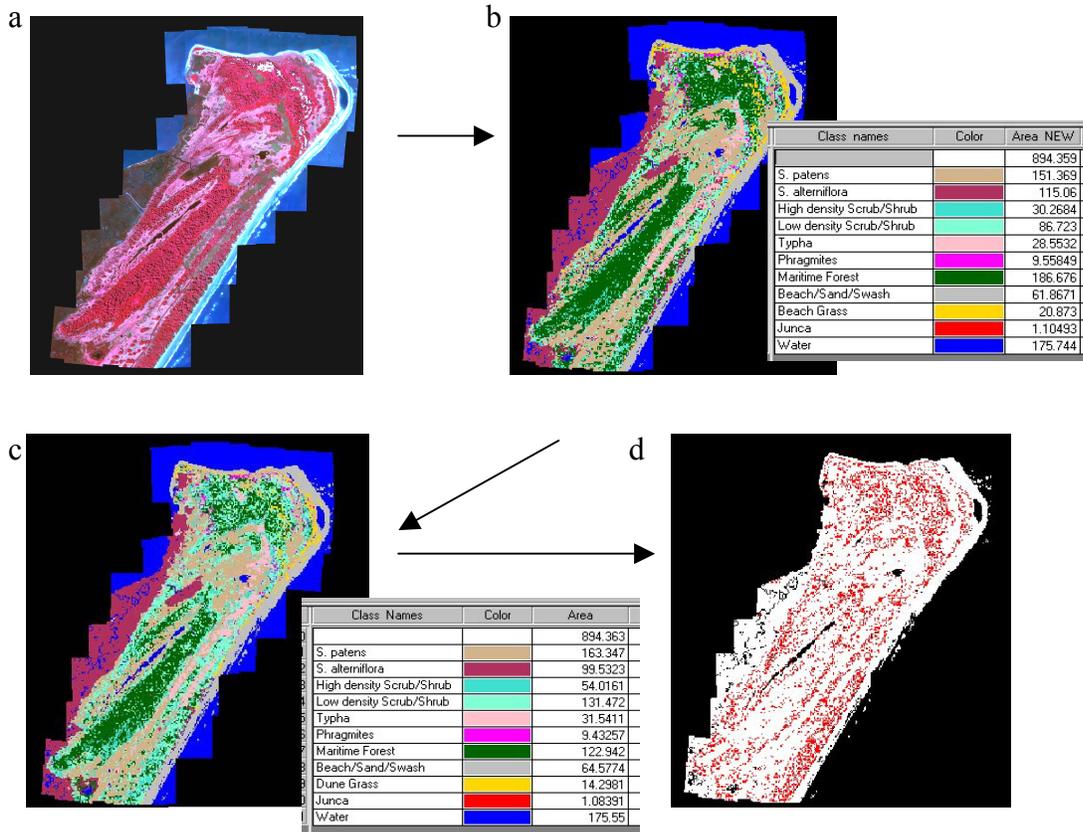


Figure 5a-d. (a) Multispectral Imagery, (b) Classification, (c) Post-Classification, and (d) Difference Map.

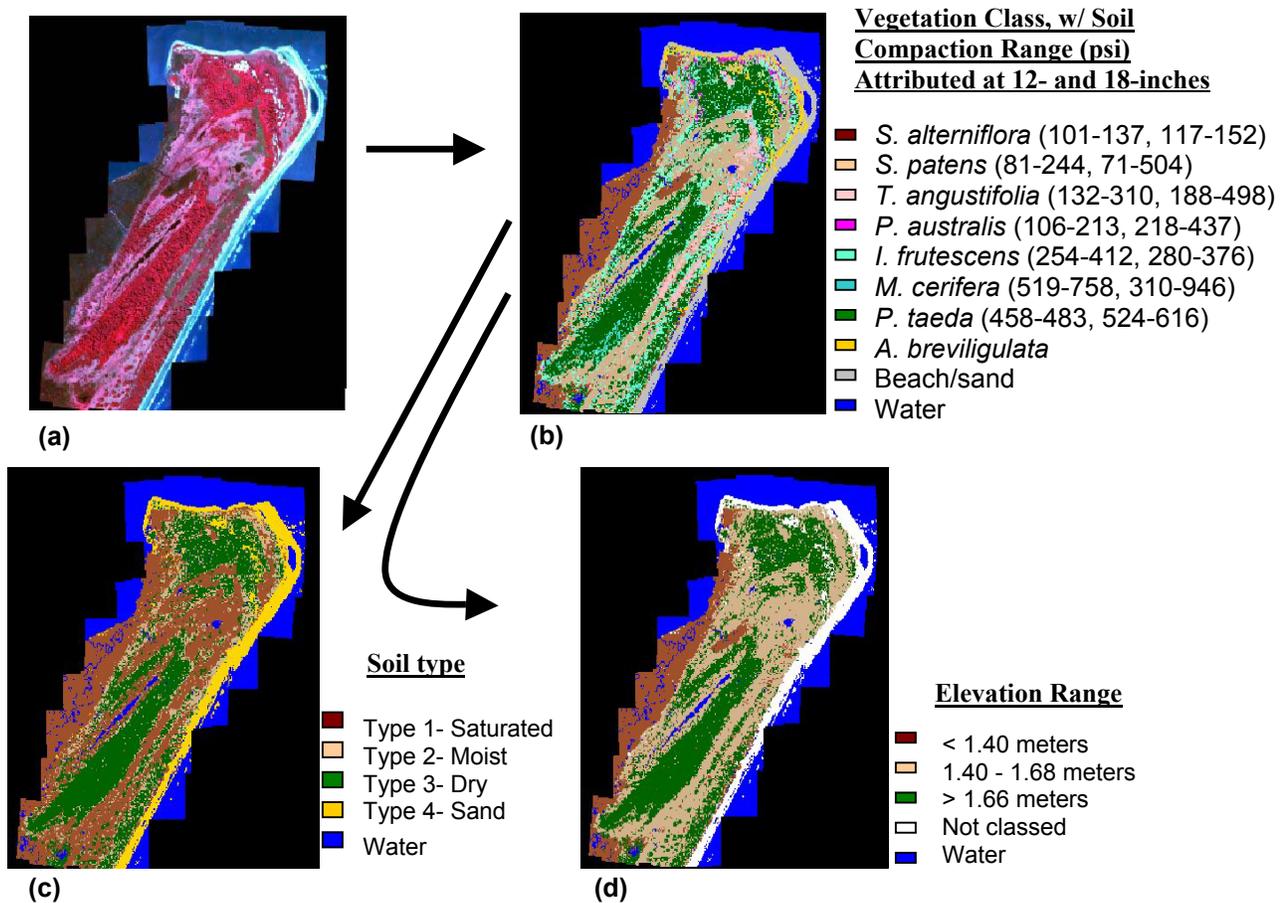


Figure 6a-d. (a) False-color Imagery, (b) Vegetation Classification, (c) Soil Type, and (d) Elevation Range.