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Regional Sediment Management Program

Development of Landscape Metrics to Support Process-Driven Ecological Modeling

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April 2014

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Abstract

Landscape pattern is an important driver in ecosystem dynamics and can control system-level functions such as nutrient cycling, connectivity, biodiversity, carbon sequestration, etc. Advances in remote sensing and Geographic Information Systems (GIS) have led to increased capability for quantifying landscape pattern, which is essential for relating spatial patterns to ecological processes.

This study analyzes GIS and remote sensing data from two time periods, 2006 and 2010, over an approximately 2-km^2 area in coastal Southwest Florida, to develop and examine landscape metrics with the goal of obtaining a better understanding of the factors that influence landscape changes observed as a result of the 2004 and 2005 hurricanes. Results are summarized by the change detection statistics and the landscape metrics, illustrating how quantitative measures can be applied to land cover data and assess both general land cover characteristics and underlying structure, aggregation, and shape characteristics. The landscape metrics analyses provided important indicators regarding the nature of the landscape changes and, thus, revealed important clues about the underlying ecological processes shaping them. This study represents an important first step in understanding how landscape metrics can be developed and in examining their potential use for linking spatial process to ecological pattern. More importantly, it also sets the stage for future research that will relate these findings to long-term ecological modeling and apply them to Engineering With Nature projects and Regional Sediment Management initiatives.

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Preface

This study was conducted for the USACE Regional Sediment Management (RSM) Program under the direction of RSM Program Manager, Linda Lillycrop. The Headquarters (HQ) USACE Program Monitor for the RSM Program at the time of this study was James E. Walker, Chief, Navigation Branch, HQ. W. Jeff Lillycrop, US Army Engineer Research and Development Center–Coastal and Hydraulics Laboratory (ERDC-CHL), was the ERDC Technical Director for Navigation. Dr. Todd S. Bridges was the ERDC Senior Research Scientist for Environmental Science.

The work was performed by the Environmental Systems Branch (EE-C) and the Wetlands and Coastal Ecology Branch (EE-W) of the Environmental Engineering Division (EE), ERDC Environmental Laboratory (ERDC-EL). At the time of publication, Scott G. Bourne was Acting Chief, CEERD-EE-C and Mark R. Graves was Acting Chief, CEERD-EE. The Deputy Director of ERDC-EL was Dr. Jack Davis and the ERDC-EL Director was Dr. Beth Fleming.

COL Jeffrey R. Eckstein was the Commander of ERDC, and Dr. Jeffery P. Holland was the Director.

Unit Conversion Factors

Multiply	By	To Obtain
cubic yards	0.7645549	cubic meters
feet	0.3048	meters
hectares	1.0 E+04	square meters
miles (nautical)	1,852	meters
miles (US statute)	1,609.347	meters

1 Introduction

Landscape pattern is an important driver in ecosystem dynamics and can control system-level functions such as nutrient cycling, connectivity, biodiversity, carbon sequestration, etc. These patterns are dynamic and evolve naturally over both ecological and evolutionary time as a result of complex, multi-scalar interactions among climatic, ecological, and geomorphological processes (Turner et al. 2001). As landscape pattern changes, ecological processes can be altered, which can affect or change the functions of the ecosystem. For example, an increase in impervious surface can result in increased potential for runoff and erosion, a decrease in water infiltration and groundwater recharge, and ultimately, a reduction in ecological productivity by decreasing water quality and replacing natural habitat. Currently, the link between process, pattern, and function remains ambiguous, which makes managing or designing ecosystem-level projects difficult. Furthermore, there is a large degree of uncertainty associated with projecting landscape dynamics into the future. As agencies move toward the more environmentally sustainable paradigm of working with, rather than against, natural processes, understanding the complexities of landscape-level interactions across scales becomes more important. For example, the US Army Corps of Engineers (USACE) Engineering With Nature (EWN) initiative is focused on designing projects that work with natural processes to create landscapes that mimic natural pattern and function, which in the long term not only reduces project costs, but also increases environmental benefits gained from a project. In order for these projects to be successful, understanding the quantitative relationship between ecological processes and landscape pattern across temporal and spatial scales is paramount. What is ultimately needed is a suite of tools that can dynamically project and link key, mechanistic patterns of landscape structure to critical ecological processes.

Advances in remote sensing and GIS have led to increased capability for quantifying landscape pattern, which is essential for relating spatial patterns to ecological processes. Understanding the relationship between ecological processes and landscape pattern is an area of ongoing focus given its necessity for predicting landscape changes (Turner 2005, Wu and Hobbs 2002). Despite the limitations inherent in the available tools and technology, numerous studies have been conducted, illustrating the use of

GIS and remote sensing to derive landscape metrics and analyze their relationship to ecological processes (Kjelland et al. 2007, Lausch and Herzog 2002, Li et al. 2005, Tischendorf 2001). Specifically, metrics are calculated from geospatial land cover data and represent quantitative measures and characteristics such as composition (i.e. types and area of individual land cover classes) and configuration (i.e. spatial arrangement of land cover classes throughout the landscape, such as habitat fragmentation) (Turner 2005).

Although research exploring the predictive capabilities of landscape metrics is lacking, the studies that have been conducted thus far reveal the importance of metrics development for enhancing the understanding of ecological processes (Lausch and Herzog 2002 Li et al. 2005, Tischendorf 2001). In general, many studies conclude that certain metrics are especially useful for examining ecological processes (i.e., number of patches in a class, average patch size, mean patch shape, and cohesion). For example, Tischendorf (2001) compared statistical relationships in a variety of landscape metrics to ecological response variables and determined that although strong correlations existed between metrics and variables (such as habitat amount), results also showed inconsistency when tested in different landscape structures. Thus, generalization of relationships is problematic. Metrics were also evaluated by Li et al. (2005) and despite some limitations related to pattern scenarios, they found utility in a set of metrics for better evaluating relationships to ecological processes. In addition, Lausch and Herzog (2002) tested a suite of metrics in a German landscape to emphasize which metrics are important for monitoring landscape change, considering issues related to map scale and extent. More research is needed to develop and analyze critical landscape metrics for an improved understanding of the factors that influence landscape change.

Although several studies have evaluated landscape metrics and their potential value for linking spatial pattern to ecological process, they have done so with limited success and illustrate the need for a better understanding of the metrics themselves and their role in long-term landscape dynamics (Lausch and Herzog 2002, Li et al. 2005, Tischendorf 2001, Turner 2005). Under such circumstances, long-term, ecologically relevant inferences are limited because the future state of the landscape is not considered. For large-scale ecosystem restoration or construction projects, the future state of the landscape must be considered, particularly under the EWN framework, in order to determine if the landscape will maintain its ecological integrity over time. Spatially-explicit ecological simulation modeling is an approach that can dynamically project both landscape pattern and ecological dynamics (Wiegand et al. 2004, Grimm et al. 2005, Swannack et al. 2009, Westervelt and Cohen 2012). This technique can therefore bridge the gap between traditional approaches in quantitative landscape ecology and the long-term projections required by project managers and monitoring agencies.

The objective of this study is to use remote sensing imagery and data to develop a variety of critical landscape metrics for a better understanding of the factors that influence landscape changes. The findings from this study will be used in future long-term research that will seek to integrate state-of-the-art remote sensing imagery, landscape analyses, and spatially-explicit ecological simulation to develop not only a better understanding of the factors that influence landscape changes, but also to develop a tool that can be used to determine how landscape structure will change as a result of EWN (and other) projects.

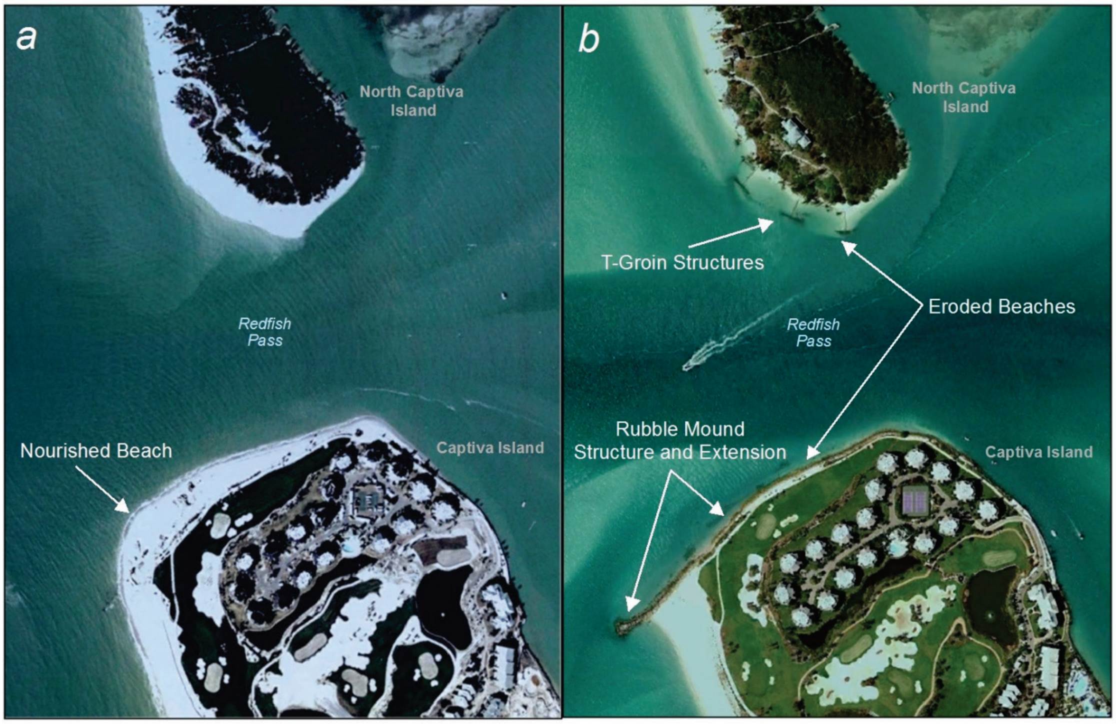
2 Methods and Data

Study area and history

A coastal area in southwest Florida (Lee County) was selected to demonstrate and quantify landscape change. Specifically, a 1.84-km^2, low-lying area including portions of two barrier islands along the Gulf of Mexico, North Captiva and Captiva Islands (Figure 1), was selected as a suitable study area. This area is highly dynamic with critically eroding beaches and captures a range of natural and developed land cover types. Redfish Pass, the channel that separates the two islands, was created by a hurricane in 1921 and is regularly dredged for depth maintenance. The channel experiences shoaling due to strong tidal currents transporting sediments and has a symmetrical north-south, tide-dominant ebb delta. A 350-ft-long rubble-mound terminal groin was constructed on the north end of Captiva Island around the channel in 1977 and rehabilitated in 2006. While three T-head groins were placed around the channel on the southern end of North Captiva Island in 1999 (Florida Department of Environmental Protection 2010), the 2006 rehabilitation included a 100-ft lengthening (Figure 2) (North Carolina Coastal Resources Commission 2010). Significant erosion of the shoreline was experienced prior to the placement of structures on both islands. Subsequent accretion has occurred along the first mile of Captiva Island as the Captiva Island Shore Protection Program includes ongoing nourishment activities. However, a 2009 study found that North Captiva Island was experiencing increasing erosion rates around the groin structures likely due to the settling of the structures (Florida Department of Environmental Protection 2010). Beach nourishment and dredging activities have impacted Captiva Island shorelines, with over 1.3 million yd^3 of material placed along the first 3 miles of the beach (North Carolina Coastal Resources Commission 2010). Beach width on both sides of the islands around the channel varies (from approximately 0 to 100 ft) due to storms, configuration changes associated with the ebb-tidal delta, and beach nourishment activities (i.e. beach nourishment widened beaches around the inlet on the north side of Captiva Island in January 2006, Figure 2). More recent imagery (Figure 2, 2010) shows that the beaches around the channel are eroded, which may be the result of less sand bypassing the terminal groin, storm events, and structure settling (Florida Department of Environmental Protection 2010, North Carolina Coastal Resources Commission 2010).

Figure 1. North Captiva and Captiva Island study area.

Figure 2. Beaches around the islands at Redfish Pass. (a) 2006 image, (b) 2010 image, showing erosion and depicting structures.

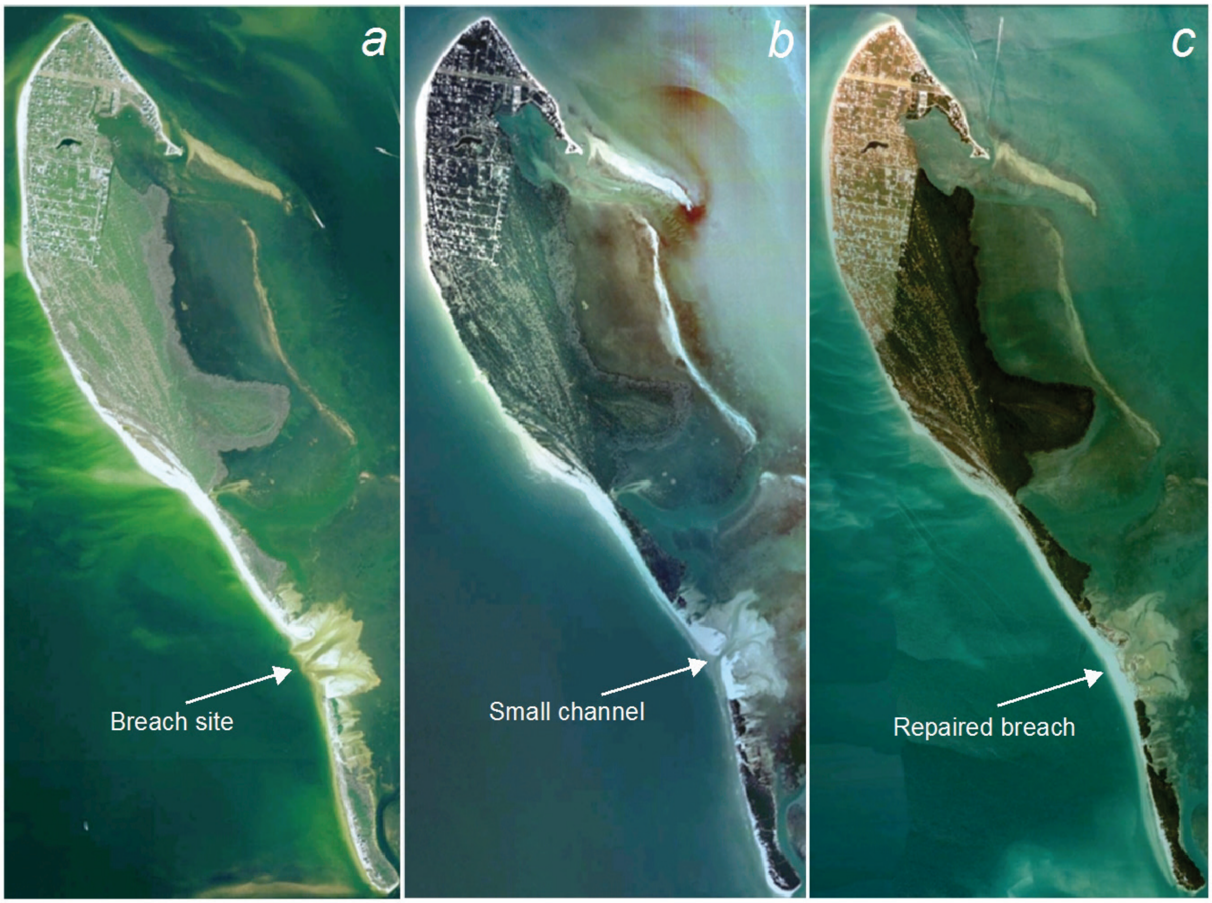


Both islands were damaged by Hurricanes Charley and Wilma in August 2004 and October 2005, respectively. North Captiva Island was breached as a result of Hurricane Charley, cutting the island in half and creating a breach that was 450 m wide and still present as a small channel in 2006 (Figure 3) (University of Rhode Island 2012). Other damage included beach erosion, dune destruction, overwash, and inundation, which moved sand across the island and into the back bay (Pine Island Sound) and destroyed coastal and wetland forest vegetation in the area. Although the breach was naturally healed in 2010 (Figure 3) with vegetation taking root to stabilize the area, it is considered highly vulnerable even to small storm events (University of Rhode Island 2012).

Data

Geospatial data used in this study were collected by the USACE Joint Airborne Lidar Bathymetry Technical Center of Expertise (JALBTCX), using their multi-sensor suite, the Compact Hydrographic Airborne Rapid Total Survey (CHARTS). CHARTS includes Optech's Scanning Hydrographic Operational Airborne Lidar Survey (SHOALS)-3000T20, with a 3-kHz bathymetric lidar and a 20-kHz topographic lidar, an Itres CASI-1500 for hyperspectral imaging, and a DuncanTech-4000 digital camera

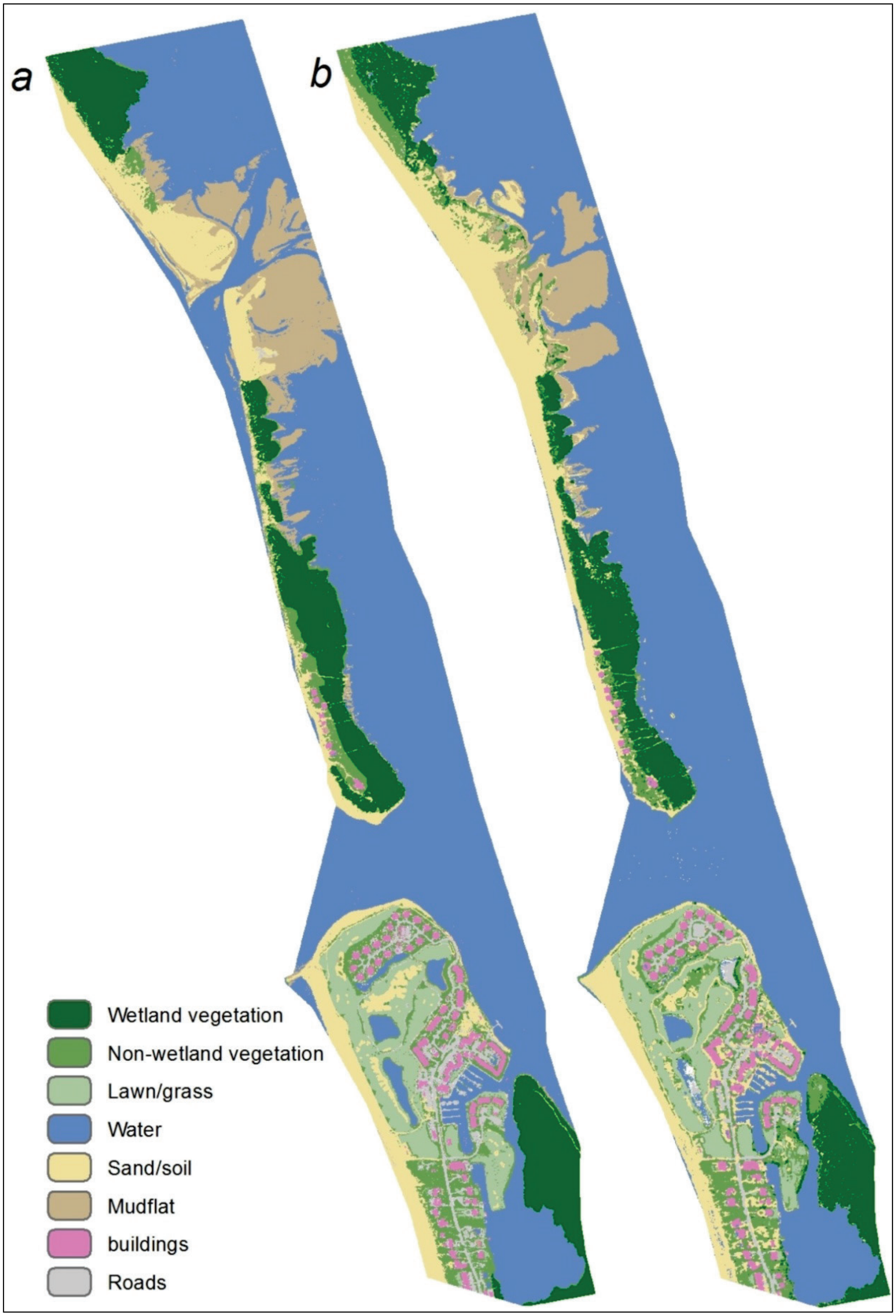
Figure 3. History of the North Captiva Island breach, which was a result of Hurricane Charley (2004). (a) site in 2004, (b) small channel in 2006, and (c) repaired in 2010.



(Wozencraft and Lillycrop 2006). In this study, light detection and ranging (lidar) elevation data and hyperspectral imagery were both used to determine land cover within the study area. Lidar is a remote sensing technology used to measure elevation, whereby a light pulse is emitted and elevation of the ground is estimated based on the pulse's time of flight between the sensor and target (Lefsky et al. 2002). In contrast, hyperspectral imagery is passively collected, in which the sensor measures reflected light energy in hundreds of narrow, contiguous bands along the electromagnetic spectrum, and they are especially useful for identifying minerals, vegetation, and other features on the Earth's surface (Lillesand et al. 2008). The combination or fusion of detailed lidar elevation data with detailed hyperspectral imagery is an emerging area of interest in the remote sensing community. This combination of data and imagery results in complementary information content, which provides a wide variety of advantages, such as the ability to distinguish features that are spectrally similar (and thus, difficult to accurately identify) and an improvement in classification accuracy (Geerling et al. 2007, Hill and Thompson 2005, Mundt et al. 2006, Reif et al. 2011, Smith et al. 2000, Wozencraft et al. 2007).

Landscape changes were analyzed using land cover data derived from hyperspectral imagery and lidar elevation data for two years (8 June 2006 and 20 July 2010). The 2006 hyperspectral imagery was collected with 0.5-m ground sample distance (GSD or pixel resolution), including 12 spectral bands with approximately 28-nanometer bandwidth in the 380-1050 nanometer spectral range. In comparison, the 2010 imagery was collected with 1-m GSD, including 36 spectral bands with 18-nanometer bandwith. The 2006 imagery was resampled to 1-m GSD using a nearest neighbor method, matching the extent and pixel resolution of the 2010 imagery for ease of comparison. The lidar elevation data were collected with a 1-m spot spacing (± 15-cm elevation accuracy), collecting values for the first and last pulse returns in a single wavelength of light at 1064 nanometers. Digital elevation models (DEMs) were developed for the topographic lidar using a variety of software, such as Applied Imagery's Quick Terrain Modeler 6.0.6 and Environmental Systems Research Institute (ESRI) ArcGIS 10.0. Hyperspectral imagery was both radiometrically and atmospherically corrected, primarily using procedures within Exelis Visual Information Solutions ENVI 4.5 software. In order to identify the major land cover types, a supervised classification approach (Maximum Likelihood) was used within the ENVI software based on selected regions of interest determined from the high-resolution imagery and ancillary data sources, including the Florida Fish and Wildlife Conservation Commission-Fish and Wildlife Research Institute's habitat geospatial data, http://research.myfwc.com. Land cover classes were refined using a post-process comparison of the Maximum Likelihood result with the DEM in ArcGIS 10.0. For example, spectral confusion between roads and buildings resulted in some buildings being misclassified as roads. However, this could be largely corrected by setting an elevation threshold above 2 m to accurately identify roads misclassified as buildings. This technique is useful for classes where an elevation difference exists, although in cases where an elevation distinction cannot be made, some confusion between classes exists (e.g. roads classified as dry sand/soil). Major land cover types present in the study area included the following: wetland vegetation (primarily mangrove swamp forest), non-wetland vegetation (scrub-shrub), lawn/grass, water, mudflat, sand/soil, buildings, and roads (Figure 4).

Figure 4. Land cover composition for (a) 2006 and (b) 2010 in the North Captiva and Captiva Island study area.



To evaluate landscape changes between the two years, the land cover classification results were compared in ENVI to develop change detection statistics (Jensen and Im 2007). Detailed statistics are generated by comparing both datasets and identifying class-for-class image differences, as well as identifying the class into which a particular pixel changed. In addition, class-level and landscape-level metrics were computed using the two land cover classification datasets in the landscape pattern analysis software, FRAGSTATS 4.0 (McGarigal et al. 2012). The software is capable of generating hundreds of patch-, class-, and landscape-level metrics to analyze landscape pattern. Typically, a subset of metrics is selected depending on the objectives of the analysis. For this study, the FRAGSTATS documentation was reviewed, along with a variety of existing studies that have extensively tested and evaluated metrics for their utility and importance in understanding ecological processes (Lausch and Herzog 2002, Li et al. 2005, Tischendorf 2001). Table 1 describes the metrics that were selected for this study.

Table 1. Description of the landscape metrics used to quantify landscape pattern and change of North Captiva and Captiva Islands from 2006 to 2010. Bold type indicates whether the index was calculated at the landscape level (Land) or/and class level (Class).

Metric	Description
Largest Patch Index (*LPI*; **Land**)	Percent of landscape occupied by the largest patch.
Class Area (*CA*; **Class**)	Total area occupied by land class type in hectares (ha).
Area-weighted mean area (*Area*; **Class**, **Land**)	Mean area of class, weighted by proportion of patch sizes within class, in hectares. Compared to standard means, the area-weighted mean is less sensitive to small patches and provides a better overall measure of class subdivision.
Clumpiness (*Clumpy*; **Class**)	Measures the degree to which a given class is aggregated given its total area. Values range from -1 to 1, with the latter representing maximum aggregation.
Area-weighted Contiguity Index (*Contig*; **Class**)	Assesses connectedness within a patch to provide an index on patch boundary configuration and thus patch shape, weighted by the area of each patch within the focal class. Values range from 0 to 1, with 1 representing maximum contiguity.
Number of Patches (*NP;* **Class, Land**)	Number of patches in the landscape of a given class.
Percent of landcover (*PLand*; **Class**)	Percentage of total landscape that a given class type occupies.
Area-weighted Shape (*Shape*; **Class**)	Complexity of patch shape compared to a standard shape (square or almost square) of the same size, weighted by patch area.

3 Results and Discussion

Land cover

Land cover areas for 2006 and 2010 are summarized in Figure 5. In general, land cover composition does not appear to change much between the two years. Overall, the buildings, roads, and lawn/grass classes appear virtually unchanged, which is expected since little new development occurred in the study area during this time. The wetland vegetation class experienced a slight decrease, while the non-wetland vegetation class experienced a slight increase. This may be due in part to some classification confusion between the two classes (Gao 1999); however, some erosion of wetland vegetation (mangrove swamp forest) on the back side of North Captiva Island is visible in the imagery and resulting classification image (Figure 6). There appears to be an increase in the sand/soil class, which primarily includes beaches. This is somewhat expected, knowing the highly dynamic nature of the beaches in this area. Visible overwash and movement of sand after the 2004 and 2005 hurricane seasons is visible in the 2006 imagery on North Captiva Island (Figure 7). The channel that existed in the 2006 imagery was absent in 2010 as sand and vegetation filled back in, naturally repairing the breached area. Although beach is lost on both islands around the inlet by 2010, some accretion and gain are experienced around the breach site and as sand is trapped by the extended portion of the rubble-mound structure on Captiva Island (Figures 2 and 7). There is a decrease in the mudflat class, which is expected given the infilling of the channel at the breach site and the changes on the back side of North Captiva Island (Figure 7). Lastly, the water class also appears largely unchanged in area, with a slight increase also likely as a result of some changes around the breach site and possibly due to some erosion and loss of beach.

Class changes

Figure 8 provides detailed information on class changes between land cover classification images on a class-for-class basis, as well as image differences between the two years. For example, although a slight decrease of the wetland vegetation class is visible in Figure 5, Figure 8 captures those details by summarizing how much of the original wetland vegetation area was lost (11%, gray bar) and how much of the class changed to another class (20%, black bar). Further examination of this class in the change detection statistics shows that most of the class change occurred between wetland vegetation and non-wetland vegetation. In short, approximately 15% (of the possible 20%) of the class change was to the non-wetland vegetation class. Some of this change can be explained by classification confusion between vegetation classes. Spectral signatures of mangrove swamp can be similar to other vegetation types and some confusion is expected (Gao 1999); however, loss or retreat of wetland vegetation can be seen between the two years (Figure 6). Damage to the wetland vegetation following the 2004 and 2005 storm seasons can have lasting effects and manifest itself over time. It is known that hurricanes damage the integrity and structure of coastal ecosystems, and in the case of forested wetlands, such as mangroves, this damage occurs to the canopy structure, increasing the amount of salt water, light, temperature, and humidity, ultimately making them vulnerable and possibly resulting in loss (Lugo 2008, Ward and Smith 2007).

Figure 5. Percent composition of landscape in 2006 and 2010 in the North Captiva and Captiva Island study area.

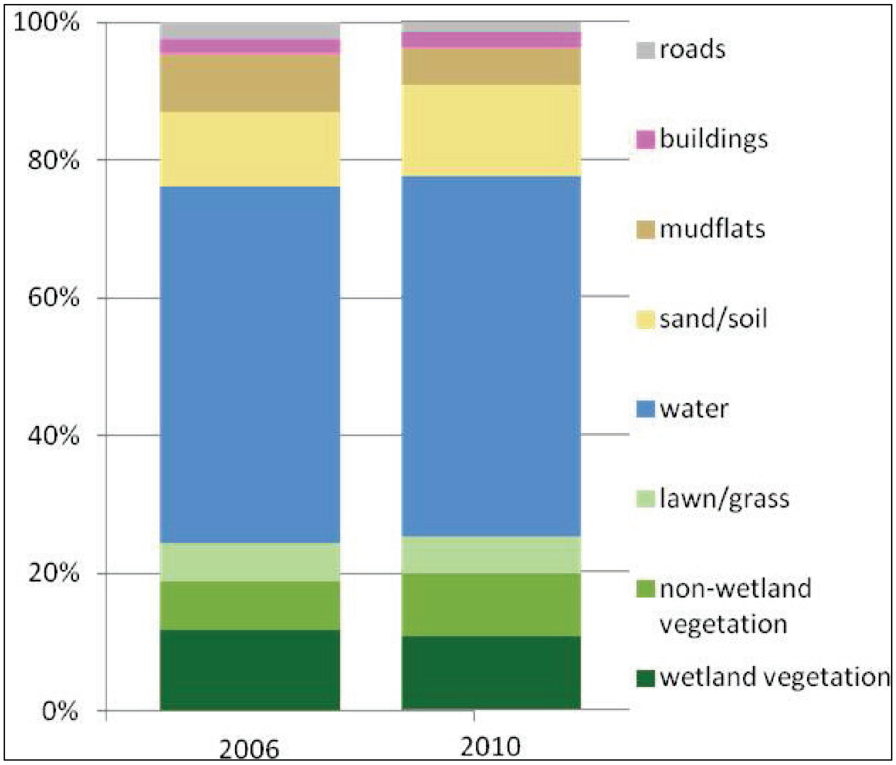


Figure 6. Retreat or erosion of wetland vegetation in two areas along the backside of North Captiva Island. The red line shows the 2006 extent of wetland vegetation overlaid onto the 2010 classification image.

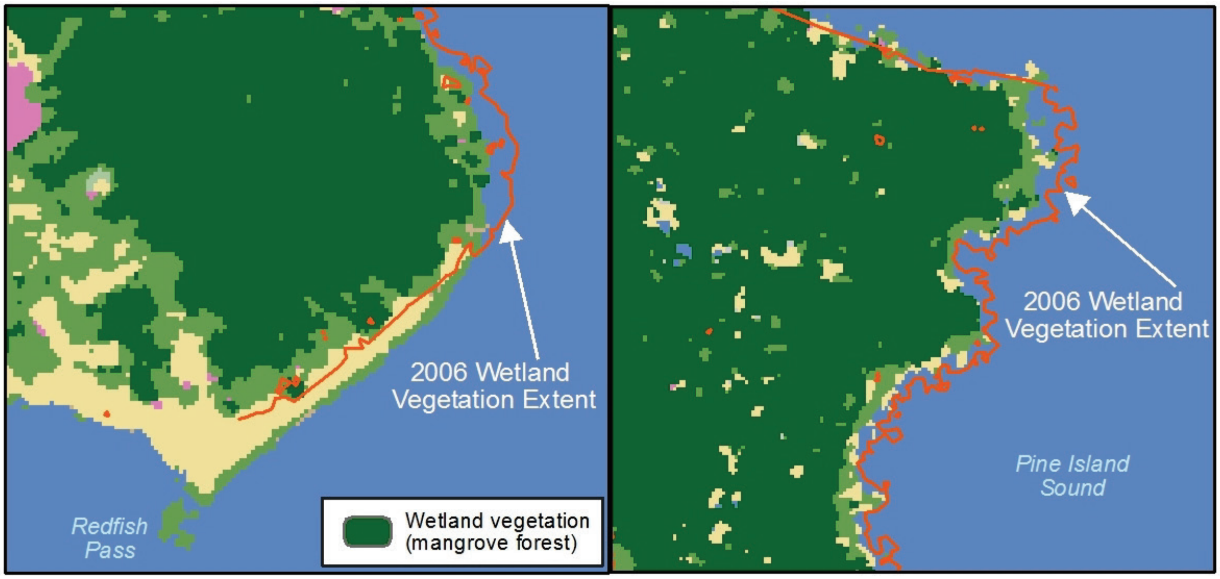


Figure 7. History of changes around the former breach site, showing a small channel, feeder channels, and overwash area in the 2006 land cover classification (a), and channel infilling, shoreline accretion, loss of mudflats, and establishment of new vegetation in the 2010 land cover classification (b).

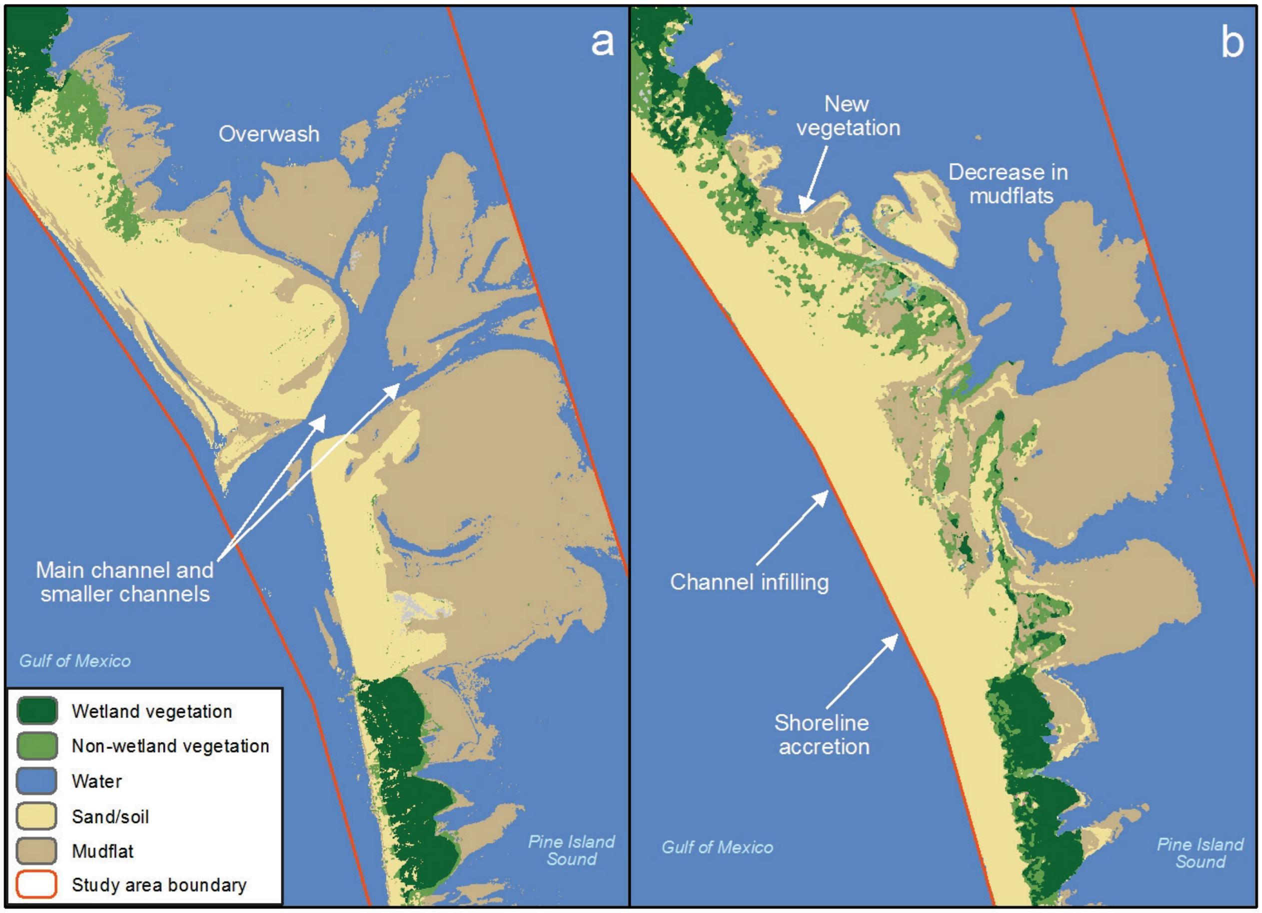
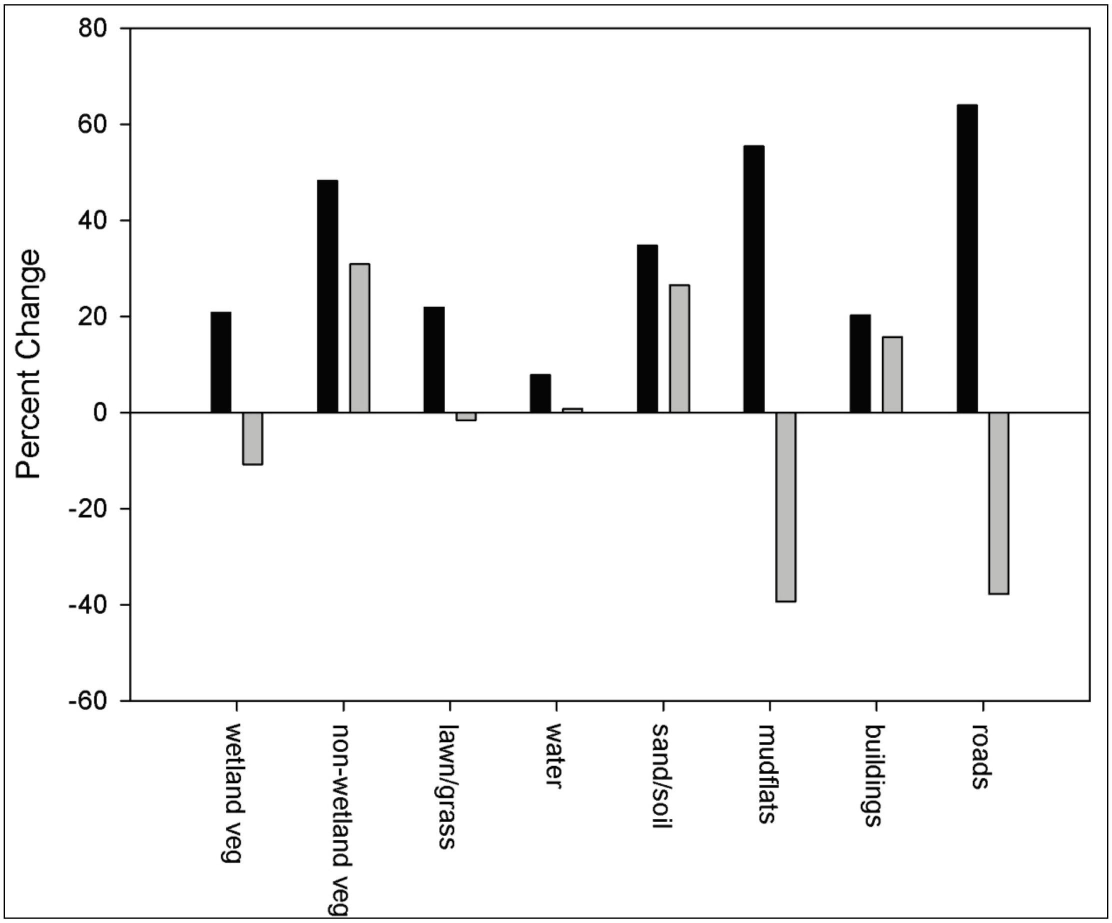


Figure 8. Percent change in land cover classes from 2006 to 2010. Black bars represent change within a particular class (e.g. 20% of wetland vegetation changed to another class between time periods). Gray bars represent overall change in area of a class between time periods (e.g. wetland vegetation lost 11% area).



The non-wetland vegetation class increased by approximately 30% in area. Again, some of this can be explained by classification confusion between vegetation types; however, establishment of new vegetation in and around the breach site is the primary reason for the increase in non-wetland vegetation area (i.e., conversion of the sand/soil and mudflat classes to the non-wetland vegetation class, Figure 7). The non-wetland vegetation class also experienced considerable changes to other classes (48%), largely due to the conversion to the sand/soil class, along select areas of the western shoreline on North Captiva Island. The sand/soil class experienced a 27% increase in area, in part due to the conversion from the mudflat class and where sand accreted along the western shoreline of North Captiva Island (especially around the breach site, Figure 7). It should be noted that there was class confusion between the roads and sand/soil classes, and thus, much of the area classified as roads in 2006 appears to change to sand/soil in 2010. This is highly unlikely and probably the result of many of the roads consisting of unconsolidated material (i.e. only major roads are asphalt or concrete) used for applications such as golf course trails, driveways, etc. This phenomenon results in class confusion. The water class had a minimal increase in area, although there was some conversion to the sand/soil class, occurring in areas where sand accreted along the shoreline (Figure 7). The mudflat class experienced a 40% decrease in area, which is especially noted around the breach site as it naturally repaired itself. Most of that loss resulted from conversion to the water class, although some is also a result of conversion to the sand/soil class (Figure 7). This might be considered somewhat of a class confusion issue because if sand/soil areas are wet, they will more closely resemble mudflats; thus, water level can be an important factor when comparing land cover. The roads class experienced a decline in area of 38%, but again, this is a result of confusion between roads and sand/soil since many of the driving surfaces on the islands consist of unconsolidated material and thus, many of the roads classified as roads in 2006 were classified as sand/soil in 2010. Lastly, the buildings class experienced a 16% increase in area, which is not likely since there was only a minimal amount of new development during this time. Some of this change can be attributed to confusion between the roads and buildings classes (i.e. highly reflective impervious surfaces can appear the same). In general, although the study area appears to change minimally between 2006 and 2010, further investigation of change detection statistics reveals that there were some notable changes in the landscape to vegetation and shoreline areas, which is consistent with the history of this dynamic coastal area and can be further explained by the landscape metrics.

Metrics change assessment

Further examination of land cover change as measured by the landscape metrics is explored in the following section. Results of the landscape-level analysis are reported in Table 2. At the landscape level, there was a 26.3% decrease in the number of patches (*NP*). The overall patch size (*LPI*) and area-weighted mean (*Area*) both increased by 39%, indicating that the landscape became less fragmented (e.g. more aggregated through a consolidation of patches) between 2006 and 2010. This is also reflected in the class-level aggregation metric (*Clumpy*) discussed below.

Table 2. Landscape-level analysis of landscape metrics for North Captiva and Captiva Islands, 2006 and 2010. Overall change is presented at the landscape level (i.e., the entire system). Metrics development analysis was performed in Fragstats 4.0. *Area*, *Contig*, and *Shape* were calculated as area-weighted metrics (see Table 1 for abbreviations).

Year/Metric	*NP*	*LPI*	*Area*
2006	10128.00	36.81	67.71
2010	7464.00	51.50	94.78
% Change	-26.30	39.91	39.98

Class-level metrics can be divided into three categories: general landscape structure (*CA*, *Area*, *NP*, *Pland*); patch aggregation (*Clumpy*); and patch shape (*Contig* and *Shape*). For each of the seven class-level metrics, each class exhibited some change between 2006 and 2010 (Table 3). That is, the landscape was not static for any class type across different measures of landscape structure.

Table 3. Class-level analysis of landscape metrics for North Captiva and Captiva Islands from 2006 and 2010. Class-level indices were divided into three categories that explained general landscape structure (General), the aggregation of patches within a class (Patch Aggregation) or the shape of a patch (Patch Shape). Metrics development analysis was performed in Fragstats 4.0. *Area, Contig, and Shape* were calculated as area-weighted metrics (see Table 1 for abbreviations).

	General								Patch Aggregation		Patch Shape			
Metric	*CA*		*NP*		*Pland*		*Area*		*Clumpy*		*Contig*		*Shape*	
Class type/year	**2006**	**2010**	**2006**	**2010**	**2006**	**2010**	**2006**	**2010**	**2006**	**2010**	**2006**	**2010**	**2006**	**2010**
Buildings	3.68	4.25	900	555	2.00	2.31	0.08	0.09	0.87	0.9	0.86	0.89	2.15	1.83
Lawn/grass	10.25	10.09	854	548	5.57	5.48	2.66	2.68	0.94	0.94	0.93	0.93	5.32	5.25
Mudflat	15.8	9.59	2725	460	8.59	5.21	3.95	2.57	0.91	0.94	0.91	0.93	5.47	5.14
Non-wetland veg.	12.79	16.75	1847	2526	6.96	9.1	0.51	0.45	0.83	0.84	0.83	0.83	6.73	5.29
Roads	4.67	2.90	1233	420	2.54	1.58	0.63	0.43	0.80	0.88	0.78	0.86	9.00	5.70
Sand/soil	19.53	24.71	1838	1659	10.62	13.43	4.11	7.05	0.92	0.92	0.92	0.92	7.55	7.11
Water	95.52	96.36	683	598	51.93	52.37	54.37	93.22	0.98	0.98	0.99	0.99	6.33	6.82
Wetland veg.	21.68	19.37	48	698	11.79	10.52	4.95	3.92	0.98	0.95	0.98	0.95	3.66	5.75

Four classes decreased in *CA*: lawn/grass, mudflat, roads, and wetland vegetation, while the others increased. Relative change for *CA* (Figure 9A) indicated that mudflats and roads lost 39% and 38% of their overall area, respectively; however, these classes occupied a relatively small part of the landscape and lost 6.21 and 1.77 ha, respectively. Conversely, the non-wetland vegetation and sand/soil classes increased by 31% and 26%, by gaining 3.96 and 5.18 ha, respectively. The number of patches (*NP*) decreased for each class type except for the non-wetland vegetation and wetland vegetation classes. The mudflat and road classes decreased the most, with the former decreasing from 2725 to 460 and the latter from 1233 to 420 (Table 2, Figure 9B). Conversely, the number of wetland vegetation patches increased from 48 to 698 (Table 3, Figure 9B). The percentage of land cover each class occupies (*PLand*) indicated that each class occupied roughly the same area in the landscape between 2006 and 2010 (Table 3). However, both the roads and mudflat classes decreased by 37.8% and 39.3%, respectively. The roads class decreased due to some class confusion between the roads and sand/soil classes (e.g. roads classified as roads in 2006 were classified as sand/soil in 2010, resulting in a decrease in the area classified as roads). In comparison, the mudflat class experienced a decrease in area due to conversion to the water and sand/soil classes, especially around the breach site (Figure 7).

Mean patch area weighted by patch size within a class (*Area*) indicated that the sand/soil and water classes had a 71% increase in mean patch size (Figure 9D). The increase in the sand/soil class from 4.11 ha to 7.05 ha is the result of the channel naturally filling in with more sand area and associated shoreline accretion along the western side of North Captiva Island (Figure 7). The mean patch size for the water class increased from 54.37 to 93.22. By 2006, the breach created by Hurricane Charley developed into a small channel with several smaller channels surrounding it; those channels were classified as water in 2006 and eventually filled in, leaving a larger patch of water behind the filled-in channel in 2010. Thus, the mean patch size for water increased, skewing *Area* towards larger patch sizes. *Area* decreased for the mudflat, non-wetland vegetation, roads, and wetland vegetation classes by over 10% (Figure 9D); however, each of these changes was less than 1 ha, indicating that the overall mean patch area, weighted by patch size, did not change significantly over the 4-year time period.

The index that calculated a measure of the degree of aggregation across the landscape (*Clumpy*) indicated, in general, that the patches within each class type were grouped together across the landscape (Table 2). That is, class types were not overly fragmented across the landscape in either 2006 or 2010. Ecologically, contiguous habitat patches reduce the overall amount of edge habitat, which is often highly correlated with increased predation and disturbance, increasing the interior/edge ratio and the average size of each patch, which can in turn increase species viability and

Figure 9. Percent change from 2006 to 2010 in values for (A) CA, (B) NP, (C) Pland, and (D) Area in the North Captiva and Captiva Island study area.

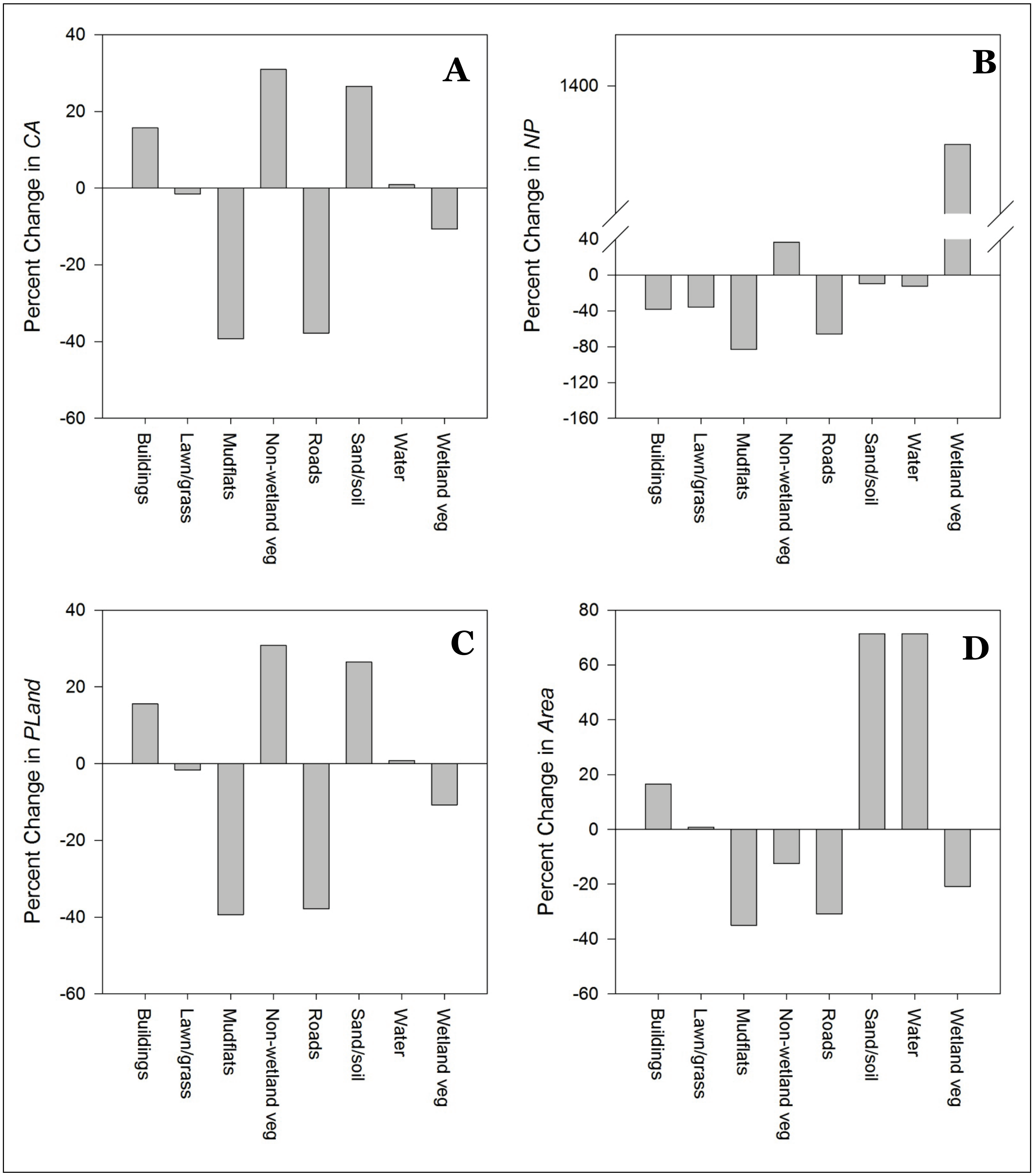
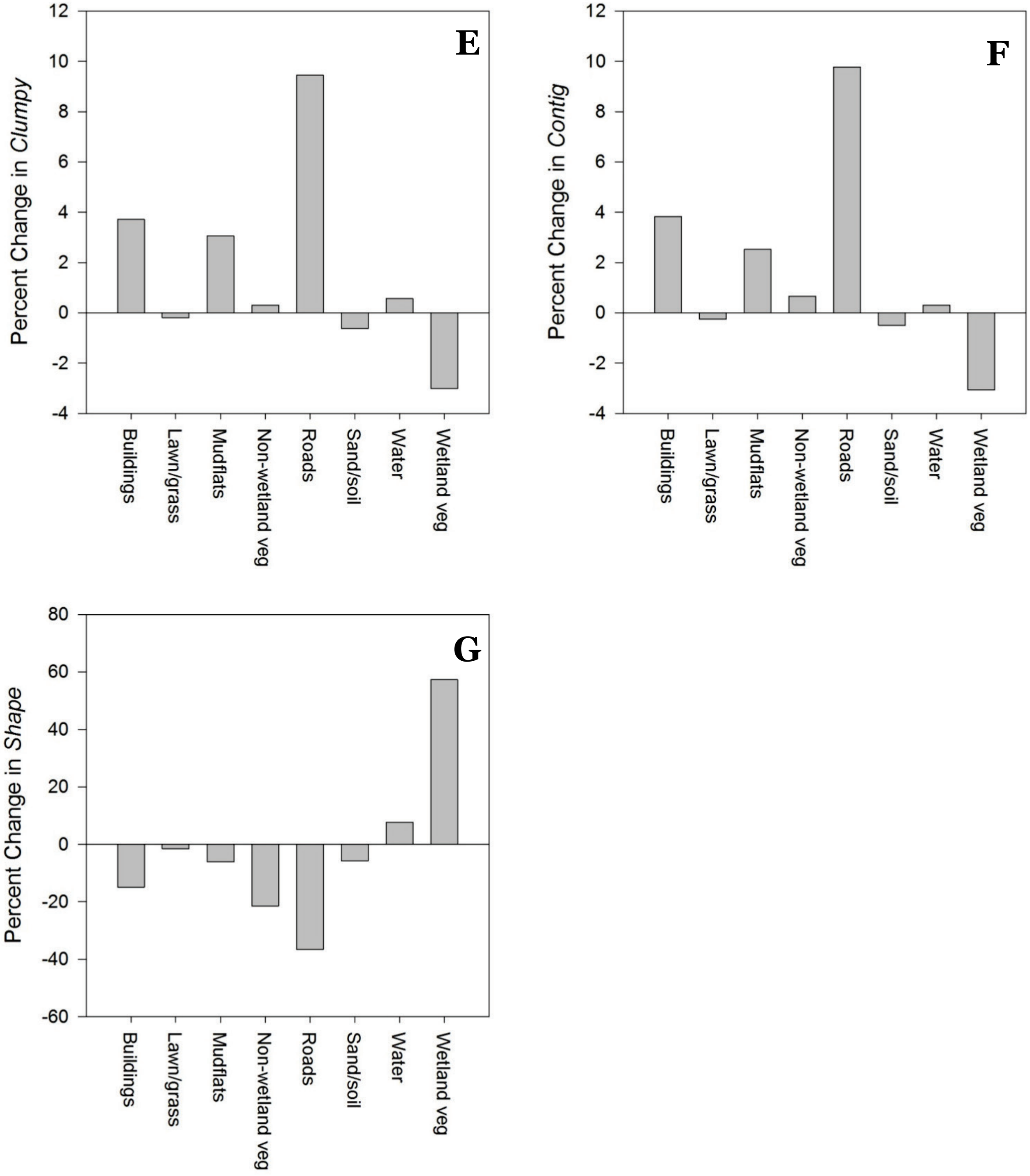


Figure 9 (Continued). Percent change from 2006 to 2010 in values for (E) *Clumpy*, (F) *Contig*, and (G) *Shape*.



persistence (Kareiva 1987). The roads class had a 10% increase in *Clumpy* (Figure 9E); however, the overall area of the road class decreased. Fewer roads were identified in the 2010 landscape (as the result of classification confusion with sand/soils) and thus, with less area classified as such, the remaining roads class became more condensed in 2010. The other class types were considered aggregated initially and remained so in 2010, each exhibiting a less than 5% change between time periods (Figure 9E).

The configuration of the patch boundary (*Contig*) did not change for most class types, although the roads class became more contiguous over time, increasing by 9.78% (Figure 9F). The remaining class types were initially close to maximum contiguity and did not exhibit much relative change between 2006 and 2010 (less than 5% for each class type) (Figure 9F). The complexity of patch shape (*Shape*) increased for the water and wetland vegetation classes (Figure 9G). The decrease in *Clumpy* for the wetland vegetation class indicated that overall patch aggregation decreased, which could likely increase the amount of edge habitat and therefore increase shape complexity. The remaining classes decreased in shape complexity, yet the roads and non-wetland vegetation classes illustrated the largest change (36.62% and 21.42%, respectively). The decrease in the road patch shape complexity is likely a result of how the roads class was classified in 2006 and 2010 and the classification confusion between them. In general, patch shape trended towards more uniformly shaped patches within each class type. The configuration of patch boundary and the complexity of the shape of the patch itself can have significant impacts on ecological dynamics. For example, as patches decrease in uniformity, edge effects increase, which can lead to changes in patch microclimate. These changes can result in exposure to sunlight and wind and greater temperature fluctuations that can lead to local extinctions of organisms, reduced dispersal and recolonization of habitat patches, and invasion of exotic or nonnative species (Turner et al. 2001).

Overall, the changes summarized in the change detection statistics and the metrics illustrate how quantitative measures can be applied to land cover data to assess general land cover characteristics, as well as underlying structure, aggregation, and shape characteristics. This comprehensive suite of change measures was assessed in the study area capturing portions of North Captiva and Captiva Islands, and depicts changes primarily associated with the 2004 and 2005 hurricane seasons evaluated in the 2006 and 2010 imagery. The original breach site in 2004 that resulted in a small channel in 2006 eventually filled in by the 2010 imagery and resulted in a reestablished shoreline with new dune vegetation (Figure 7). This change in landscape structure is also a good example of how the general change detection statistics can be combined with the metrics to examine changes holistically. Thus, the changes seen in Figure 7 can be captured and evaluated in a variety of complementary ways illustrated in some of the following change detection statistics and metrics:

1. The sand/soil class increased by 27% as the channel repaired itself and large sections of shoreline were reestablished. The patches within the class became much larger in size (indicated by increases in *CA*, *PLand*, and *Area*), which decreased the overall number of patches (*NP*) and resulted in a decline in overall patch complexity (decreases in *Contig* and *Shape*) and aggregation (decrease in *Clumpy*).
2. The 40% decrease in the mudflat class area occurred primarily due to conversion to the sand/soil and water classes around the repaired channel. The amount and complexity of the mudflat class decreased (decreases in *CA, NP, PLand, Area,* and *Shape*) as the channel repaired itself. Conversely, what is left of that class is more aggregated and contiguous in terms of patch connectivity (increases in *Clumpy* and *Contig*).
3. The non-wetland vegetation class increased by 30% as a result of new vegetation being established around the repaired channel, indicated by increases in *CA* and *Pland*. The habitat became slightly more aggregated and connected overall (increases in *Clumpy and Contig*); however, the new habitat patches tended to be slightly smaller in size (decrease in *NP*) and less complex in terms of patch shape (decrease in *Shape*).
4. The amount of the water class only slightly increased (increases in *CA* and *Pland*), although there was a marked increase in the patch size area (increase in *Area*). Thus, the smaller channels identified as water in 2006 disappeared with the infilling of the channel, leaving behind much larger, contiguous, less complex patches (increases in *Clumpy*, *Contig,* and *Shape*) behind the breach/channel. This is also illustrated by a decrease in the number of patches, further revealing that by 2010, fewer larger patches were left (decrease in *NP*).

Combining general change detection statistics with information about the configuration and composition of the landscape (derived from landscape metrics) provides a more comprehensive and holistic view than either type of information provides alone. Although the change detection statistics provide useful information about class-to-class conversions, the landscape metrics analyses provide important indicators regarding the nature of those changes. Thus, the landscape metrics analyses reveal important clues about the underlying ecological processes shaping them. Together, the statistics and metrics provide critical information about the landscape and, more importantly, a better understanding of the factors that influence landscape changes.

4 Conclusions and Future Research

Results of this study showed that coastal landscape patterns can change in short periods of time and, more importantly, that those changes can be quantified through the use of landscape metrics. For example, when the breach on North Captiva Island was created by Hurricane Charley in 2004, a loss of beach and vegetative habitat was still apparent in the 2006 imagery; however, natural hydrodynamic and environmental processes filled and revegetated the channel within 6 years, restoring the wildlife habitat to what one can assume is more reflective of natural conditions. The landscape metrics illustrated the range of changes in landscape structure, aggregation, and shape, highlighting underlying changes to the shoreline and vegetation, especially around the breach site between the two years. Despite demonstrating landscape changes, one limitation of this study is the temporal frequency of the data (e.g. two image dates, 4 years apart). Thus, it is not possible to make inferences about the long-term future dynamics of this system given that limitation. This issue is common for landscape studies that are limited to data availability. However, advances in remote sensing and decreases in costs have resulted in imagery and data with increased temporal and spatial resolutions and have improved capabilities for evaluating landscape changes. It has been noted that spatial resolution can also be a limiting factor in land cover data. In order to capture certain phenomena in the landscape (e.g. habitat corridors), a spatial resolution of 5 m or less is necessary (Lausch and Herzog 2002). Higher spatial resolution imagery is also becoming increasingly available through improved spaceborne and airborne platforms. Future research should consider the availability of data and take advantage of the improved spatial and temporal resolutions to continue evolving the understanding of landscape metrics and linking them to ecological processes.

Spatial simulation offers the ability to project landscape dynamics and to simulate spatial patterns across long time periods. However, in order for spatial simulation to be applied usefully, particularly for EWN projects, there needs to be a strong, quantitative link between landscape pattern and ecological dynamics to give project managers tools to capture system level dynamics accurately. Currently, understanding how ecological processes interact with landscape pattern is a major research focus in landscape ecology (Naiman and Rogers 1997, Augustine and Frank 2001, Lundberg and Moberg 2003). The general consensus is that holistic, landscape-level studies provide enhanced opportunities for linking populations, ecosystem processes, and services (Turner 2005). Future research, therefore, needs to include developing approaches that can explain cause-effect relationships between pattern and process.

Agent-based modeling (Grimm and Railsback 2005, Railsback and Grimm 2012) is a promising approach that can capture how organisms interact with a dynamic environment. These models are powerful tools because they are process-driven and focused on two or more levels of interactions (e.g., species interacting with a landscape). These models differ from traditional ecological models, such as Lotka-Volterra (Lotka 1925, Volterra 1926), matrix (Caswell 2001), or system dynamics models (Ford 1999, Grant and Swannack 2008) because they explicitly represent how individuals (i.e., agents) and the environmental variables that affect them vary over space, time, and other dimensions (Railsback and Grimm 2012). Another benefit of this approach is that it allows important processes and cause-effect relationships to be included that are often too complex to include in simpler models. For example, this approach has been used to model shorebird population response to loss of mudflat habitat (Goss-Custard et al. 2006), land pattern, and spatial heterogeneity impact on foraging habitat of migratory birds (Railsback and Johnson 2011), and endangered species response to various changes in environmental factors (Wiegand et al. 2003, Westervelt and Cohen 2012).

Agent-based approaches are not necessarily limited to ecological phenomena and have been successfully applied to determine factors controlling patterns of land use change during urban sprawl, the ways in which those patterns are affected by policy decisions (Parker et al. 2003, Brown et al. 2004), and the interaction of patterns in multiple economic and social settings (Railsback and Grimm 2012). Given the flexibility of this approach, it seems promising for developing coupled landscape-evolution and process-driven ecological models. More specifically, if quantitative relationships can be established between landscape pattern formation and environmental or geomorphic processes, then those relationships could drive a landscape evolution submodel, and ecological agents could then be integrated into the virtual landscape with their dynamics being projected into the future.

One major issue that is often encountered with agent-based approaches is scaling (Ludwig et al. 2000; Groffman et al. 2006). More specifically, how organisms scale their responses to heterogeneous landscape patterns remains ambiguous and a considerable amount of uncertainty is associated with scaling responses in ecology. Spatially explicit, agent-based models can be designed to simulate processes across scales. Future research should include developing models that explicitly simulate scalar processes, and if the appropriate evaluation techniques, such as pattern-oriented modeling (Grimm et al. 2005) are used, then this uncertainty can be significantly reduced, making the model more robust. Finally, given the need to assess multiple project scenarios and determine environmental benefits from those projects, future modeling efforts should include not only the ability to compare multiple scenarios, but also the ability to quantify benefits for each. For example, in this project, the breach repair (Figure 7) increased both non-wetland vegetation and sand/soil habitats; however, while an increase in habitat area could be quantitatively documented, system-level benefits of the landscape change were not assessed. Future research should incorporate ways in which landscape metrics can inform environmental benefits analysis for different project scenarios at the landscape level.

As the field of landscape ecology evolves and remote sensing and GIS technology improve, new opportunities for examining landscape metrics and their ability to illustrate and explain patterns and processes are becoming increasingly available. This study represents an important first step in understanding how landscape metrics can be developed and examining their potential use for linking spatial process to ecological pattern. More importantly, it also sets the stage for future research that will aim to relate these findings to long-term ecological modeling and application to EWN projects.

References

Augustine, D. J., and D. A. Frank. 2001. Effects of migratory grazers on spatial heterogeneity of soil nitrogen properties in a grassland ecosystem. *Ecology* 82:3149-3162.

Brown, D. G., S. E. Page, R. Riolo, and W. Rand. 2004. Agent-based and analytical modeling to evaluate the effectiveness of greenbelts. *Environmental Modelling & Software* 19:1097-1109.

Caswell, H. 2001. *Matrix population models: Construction, analysis, and interpretation*. 2nd ed. Sunderland, MA: Sinauer Associates.

Florida Department of Environmental Protection. 2010. North Captiva T-Groin Maintenance. ftp://ftp.dep.state.fl.us/pub/ENV-PRMT/lee/issued/0124948_North_Captiva_T-Groin_Repair/006-JC/Intent%20to%20Issue/Kohler%20Groin%20Maint%20Intent%20%285-27-10%29.pdf. Date Accessed: September 25, 2012.

Ford, A. 1999. *Modeling the environment: An introduction to system dynamics modeling of environmental systems*. Washington, DC: Island Press.

Gao, J. 1999. A comparative study on spatial and spectral resolutions of satellite data in mapping mangrove forests. *International Journal of Remote Sensing* 20:2823-2833.

Geerling, G. W., M. Labrador-Garcia, J. G. P. W. Clevers, A. M. Ragas, and A. J. M. Smits. 2007. Classification of floodplain vegetation by data fusion of spectral (CASI) and Lidar data. *International Journal of Remote Sensing* 28: 4263-4284.

Goss-Custard, J. D., N. H. K. Burton, N. A. Clark, P. N. Ferns, S. McGrorty, C. J. Reading, M. M. Rehfisch, R. A. Stillman, I. Townend, A. D. West, and D. H. Worrall. 2006. Test of a behavior-based individual-based model: Response of shorebird mortality to habitat loss. *Ecological Applications* 16:2215-2222.

Grant, W. E., and T. M. Swannack. 2008. *Ecological modeling: A common-sense approach to theory and practice*. Oxford, UK: Blackwell Publishing.

Grimm, V., and S. F. Railsback. 2005. *Individual-based modeling and ecology*. Princeton, NJ: Princeton University Press.

Grimm, V., E. Revilla, U. Berger, F. Jeltsch, M. W. Mooij, S. F. Railsback, H. H. Thulke, J. Weiner, T. Wiegand, and D. L. DeAngelis. 2005. Pattern-oriented modeling of agent-based complex systems: Lessons from ecology. *Science* 310:987-991.

Groffman, P.M., J. S. Baron, T. Blett, A. J. Gold, I. Goodman, L. H. Gunderson, B. M. Levinson, M. A. Palmer, H. W. Paerl, G. D. Peterson, N. L. Poff, D. W. Rejeski, J. F. Reynolds, M. G. Turner, K. C. Weathers, and J. Wiens. 2006. Ecological thresholds: The key to successful environmental management or an important concept with no practical application? *Ecosystems* 9:1-13.

Hill, R. A., and A. G. Thompson. 2005. Mapping woodland species composition and structure using airborne spectral and lidar data. *International Journal of Remote Sensing* 26:3763-3779.

Jensen, J. R. and J. Im. 2007. Remote sensing change detection in urban environments. In *Geo-Spatial Technologies in Urban Environments,* ed. J. R. Jensen, J. D. Gatrell, and D. Mclean, 7-31. Berlin: Springer.

Kareiva, P. 1987. Habitat fragmentation and the stability of predator-prey interactions. *Nature* 326:388-390.

Kjelland, M. E., U. P. Kreuter, G. A. Clendenin, R. N. Wilkins, X. B. Wu, E. G. Afanador, and W. E. Grant. 2007. Factors related to spatial patterns of rural land fragmentation in Texas. *Environmental Management* 40:231-244.

Lausch, A., and F. Herzog. 2002. Applicability of landscape metrics for the monitoring of landscape change: Issues of scale, resolution, and interpretability. *Ecological Indicators* 2:3-15.

Lefsky, M. A., W. B. Cohen, G. G. Parker, and D. J. Harding. 2002. Lidar Remote Sensing for Ecosystem Studies. *Bioscience* 52:19-30.

Li, X.; S. H. Hong, B. Rencang, W. Qingchun, C. Yu, H. Yuanman, and L. Yuehui. 2005. The adequacy of different landsape metrics for various landscape patterns. *Pattern Recognition* 38:2626-2638.

Lillesand, T. M., R. W. Kiefer, and J. W. Chipman. 2008. *Remote sensing and image interpretation*. 6th ed. Hoboken, NJ: John Wiley & Sons.

Lotka, A. J. 1925. *Elements of physical biology*. New York: Dover Publications.

Ludwig, J. A., J. A. Wiens, and D. J. Tongway. 2000. A scaling rule for landscape patches and how it applies to conserving soil resources in savannas. *Ecosystems* 3:84-97.

Lugo, A. E. 2008. Visible and invisible effects of hurricanes on forest ecosystems: An international review. *Austral Ecology* 33:368-398.

Lundberg, J., and F. Moberg. 2003. Mobile link organisms and ecosystem functioning: Implications for ecosystem resilience and management. *Ecosystems* 6: 87-98.

McGarigal, K., S. A. Cushman, and E. Ene. 2012. FRAGSTATS v4: Spatial pattern analysis program for categorical and continuous maps. Computer software program produced by the authors at the University of Massachusetts, Amherst. Available at: http://www.umass.edu/landeco/research/fragstats/fragstats.html

Mundt, J. T., D. R. Streutker, and N. F. Glenn. 2006. Mapping sagebrush distribution using fusion of hyperspectral and lidar classifications. *Photogrammetric Engineering & Remote Sensing* 72:47-54.

Naiman, R. J., and K. H. Rogers. 1997. Large animals and system-level characteristics in river corridors. *BioScience* 47:521-529.

North Carolina Coastal Resources Commission. 2010. *Final Report: Terminal groin study*. http://dcm2.enr.state.nc.us/CRC/tgs/finalreport.html. Date Accessed: September, 25, 2012.

Parker, D. C., S. M. Manson, M. A. Janssen, M. J. Hoffmann, and P. Deadman. 2003. Multi-agent systems for the simulation of land-use and land-cover change: A review. *Annals of the Association of American Geographers* 93:314-337.

Railsback, S. F., and M. D. Johnson. 2011. Pattern-oriented modeling of bird foraging and pest control in coffee farms. *Ecological Modelling* 222:3305-3319.

Railsback, S. F., and V. Grimm. 2012. *Agent-based and individual-based moeling: A practical introduction*. Princeton, NJ: Princeton University Press.

Reif, M. K., L. M. Dunkin, J. M. Wozencraft, and C. L. Macon. 2011. Sensor fusion benefits complex coastal mapping. *Earth Imaging Journal* 8(2):32-35.

Smith, R. A., J. L. Irish, and M. Q. Smith. 2000. Airborne lidar and airborne hyperspectral imagery: A fusion of two proven sensors for improved hydrographic surveying. *Proceedings of Canadian Hydrographic Conference* (Montreal, Canada).

Swannack, T. M., W. E. Grant, and M. R. J. Forstner. 2009. Projecting population trends of endangered amphibian species in the face of uncertainty: A pattern-oriented approach. *Ecological Modelling* 220:148-159.

Tischendorf, L. 2001. Can landscape indices predict ecological processes consistently? *Landscape Ecology* 16:236-254.

Turner, M. G. 2005. Landscape ecology: What is the state of the science? *Annual Review of Ecology, Evolution, and Systematics* 36:319-344.

Turner, M. G., R. H. Gardner, and R. V. O'Neill. 2001. *Landscape ecology in theory and practice: Pattern and process*. New York: Springer.

University of Rhode Island. 2012. Hurricanes: Science and Society, Terrestrial Impacts. http://www.hurricanescience.org/society/impacts/environmentalimpacts/terrestrialimpacts/. Date Accessed: September 25, 2012.

Volterra, V. 1926. Fluctuations in the abundance of a species considered mathematically. *Nature* 118:558-560.

Ward, G. A., and T. J. Smith, III. 2007. Predictive mangrove forest recovery on the southwest coast of Florida following the impact of Hurricane Wilma, October 2005. In*: Science and the Storms: The USGS Response to the Hurricanes of 2005*. USGS Circular 1306.

Westervelt, J. D., and G. L. Cohen, ed. 2012. *Ecologist-developed spatially explicit dynamic landscape models*. New York: Springer.

Wiegand, T., E. Revilla, and F. Knauer. 2004. Dealing with uncertainty in spatially explicit population models. *Biodiversity and Conservation* 13:53-78.

Wiegand, T., F. Jeltsch, I. Hanski, and V. Grimm. 2003. Using pattern-oriented modeling for revealing hidden information: A key for reconciling ecological theory and application. *Oikos* 100:209-222.

Wozencraft, J. M., and W. J. Lillycrop. 2006. JALBTCX Coastal Mapping for the USACE. *International Hydrographic Review* 7:28-37.

Wozencraft, J. M., C. L. Macon, and W. J. Lillycrop. 2007. CHARTS-Enabled Data Fusion for Coastal Zone Characterization. *Proceedings of the Sixth International Symposium on Coastal Engineering and Science of Coastal Sediment Processes 2007* (Reston, Virginia, USA, ASCE): 1827-1836.

Wu, J., and R. Hobbs. 2002. Key issues and research priorities in landscape ecology: An idiosyncratic synthesis. *Landscape Ecology* 17:355-365.

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14. ABSTRACT
Landscape pattern is an important driver in ecosystem dynamics and can control system-level functions such as nutrient cycling, connectivity, biodiversity, carbon sequestration, etc. Advances in remote sensing and Geographic Information Systems (GIS) have led to increased capability for quantifying landscape pattern, which is essential for relating spatial patterns to ecological processes. This study analyzes GIS and remote sensing data from two time periods, 2006 and 2010, over an approximately 2-km^2 area in coastal Southwest Florida, to develop and examine landscape metrics with the goal of obtaining a better understanding of the factors that influence landscape changes observed as a result of the 2004 and 2005 hurricanes. Results are summarized by the change detection statistics and the landscape metrics, illustrating how quantitative measures can be applied to land cover data and assess both general land cover characteristics and underlying structure, aggregation, and shape characteristics. The landscape metrics analyses provided important indicators regarding the nature of the landscape changes and, thus, revealed important clues about the underlying ecological processes shaping them. This study represents an important first step in understanding how landscape metrics can be developed and in examining their potential use for linking spatial process to ecological pattern. More importantly, it also sets the stage for future research that will relate these findings to long-term ecological modeling and apply them to Engineering With Nature projects and Regional Sediment Management initiatives.

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