proceedings

Proceedings

An Automated Model to Classify Barrier Island Geomorphology Using Lidar Data †

Joanne N. Halls [1,*], Maria A. Frishman [1] and Andrea D. Hawkes [2]

[1] Department of Earth and Ocean Sciences, University of North Carolina Wilmington, 601 S. College Rd., Wilmington, NC 28403, USA; maria.a.frishmancarver.mil@mail.mil
[2] Department of Earth and Ocean Sciences & Center for Marine Science, University of North Carolina Wilmington, 601 S. College Rd., Wilmington, NC 28403, USA; hawkesa@uncw.edu
* Correspondence: hallsj@uncw.edu; Tel.: +1-910-962-7614

† Presented at the 2nd International Electronic Conference on Remote Sensing, 22 March–5 April 2018; Available online: https://sciforum.net/conference/ecrs-2.

Published: 22 March 2018

Abstract: Limited research has studied the use of Lidar in mapping coastal geomorphology. The purpose of this project was to build on existing research and develop an automated modeling approach to classify the coastal geomorphology of barrier islands and test this at four sites in North Carolina. Barrier islands are shaped by natural coastal processes, such as storms and longshore sediment transport, as well as by human influences, such as beach nourishment and urban development. An automated geomorphic classification model was developed to classify Lidar data into 10 geomorphic types over four time-steps from 1998 to 2014. Tropical storms and hurricanes had the most influence on change and movement. On the developed islands, there was less influence of storms, owing to the inability of features to move because of coastal infrastructure. Beach nourishment was the dominant influence on developed beaches, because this activity ameliorated the natural tendency of an island to erode. Understanding how natural and anthropogenic processes influence barrier island geomorphology is critical to predicting an island's future response to changing environmental factors such as sea-level rise. The development of an automated model equips policy makers and coastal managers with information to make development and conservation decisions, and the model can be implemented at other barrier islands.

Keywords: Lidar; barrier island; coastal geomorphology; feature movement

1. Introduction

Beautiful beaches and expensive properties are found on barrier islands, which are features that parallel the coastline and protect the mainland from waves and storms. Their location and sandy composition make barrier islands both economically valuable and physically vulnerable. Studies have shown that, over 5 years, a barrier island can migrate over 100 m and experience a 50% change in volume [1,2]. Understanding the evolution of barrier island geomorphology can assist policy makers and coastal managers with decisions regarding future land-use development. In North Carolina, the entire coastline is fronted by a chain of barrier islands. A typical barrier island system is composed of a gently sloping continental shelf, a sandy island, and a back-barrier marsh that extends into an estuary; individual barrier islands are separated by tidal inlets [3].

Lidar data have been used to study coastal morphology [1,2,4–8]. In these studies, Lidar and other data (such as aerial photography) have been used to map shorelines and marshes, but to our knowledge there has not been a study that has developed an automated method for classifying all geomorphic types on a barrier island. This project developed a model that classifies barrier island features from Lidar data and tested this approach on four islands in North Carolina (Figure 1). The second objective was to quantify change over time and correlate the results with human and environmental processes. The North Carolina coast has a diverse chain of barrier islands. In particular, the barrier islands in the southern part of the state are distinctively different from those in the north, which is largely due to differences in subsurface geology and coastline orientation [9].

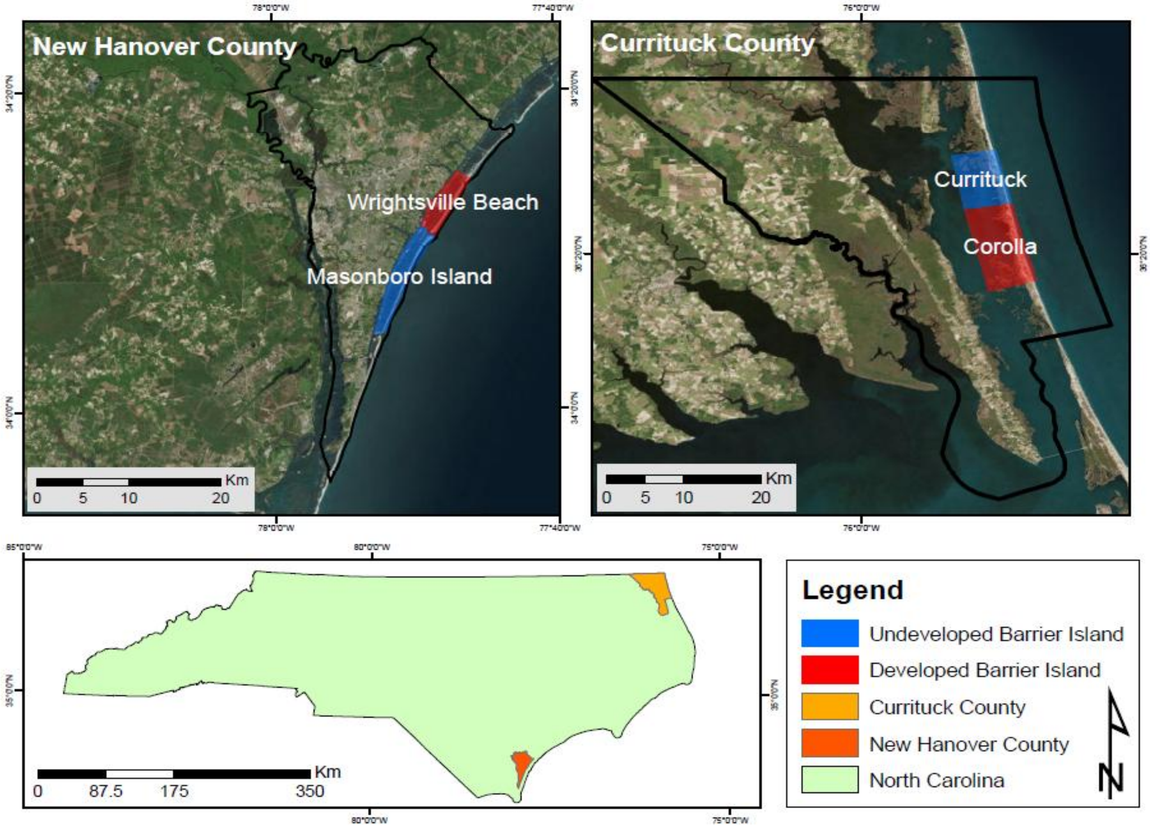

Figure 1. Study areas: Wrightsville Beach and Masonboro Island are located in New Hanover County in southern North Carolina (NC), and Currituck and Corolla are in Currituck County in the north.

2. Methods

The following geomorphic feature types were studied: (1) Intertidal: region that is inundated daily because of tides; (2) Supratidal: region that is inundated occasionally because of astronomically high tides or severe weather events; (3) Dunes: linear features that run parallel to the shoreface and have the highest elevation; (4) Hummock: relic dune located behind the primary dune, at a lower elevation than dunes but at a higher elevation than other surrounding features, having a round shape; (5) Overwash: slightly elevated and flat areas located in the back barrier; (6) Swale: low depressions located between dunes and upland areas; (7) Channel: low depressions, cut by water, located adjacent to the supratidal region; (8) Upland: flat portions of the barrier island, behind the primary dune.

Fieldwork was conducted from May to December 2016 to collect ground control points (GCPs) to test the model classification accuracy. Each study area was segmented by transects, cast 100 m apart, perpendicular to the island centerline. GCPs were collected using a Trimble 5800 series Real Time Kinematic (RTK) GPS along 25 randomly selected transects per study area. Along each transect, the center of each geomorphic feature was recorded with position and elevation (X, Y, Z), feature type, and a GoPro Hero2 was used to collect videos. The Trimble RTK has 10 cm horizontal and 20 cm vertical accuracy when the data is collected in "stakeout" mode. The GCPs were post-processed in Trimble Office, exported as CSV files, and imported into ArcGIS.

Lidar data was acquired from NOAA's Digital Coast using the Data Access Viewer tool (www.coast.noaa.gov/dataviewer/#/lidar/search/). Each dataset was examined for point spacing and accuracy, and the highest quality datasets were used in this study. Different datasets were used for the northern and southern areas because no single data covered all four areas. For Masonboro and

Wrightsville, the Lidar dates were: 1998, 2005, 2010, and 2014, and for Currituck and Corolla: 2001, 2005, 2009, and 2014. Research has tested the spatial resolution for examining volume change in coastal features and determined that 1–2 m is optimal [10]; the inverse distance weighted (IDW) interpolation technique was the best for producing raster surfaces [11,12]. After spatial sensitivity tests were conducted, Lidar ground returns were interpolated using IDW with a 10-point search and maximum 10 m radius to create Digital Elevation Models (DEMs) with a 1 × 1 m cell size. DEM accuracy was tested by comparing interpolated elevation values to field collected GCP data. An average elevation difference of less than 10 cm was considered acceptable on the basis of RTK accuracy and the time span from Lidar data collection to fieldwork (2 years). For developed areas (Wrightsville and Corolla), anthropogenic features were extracted from the ground return DEM prior to classifying the geomorphic features.

The automated classification model consists of a series of steps that identified the unique characteristics of each type of geomorphic feature (Table 1). The model requires four inputs: (1) a DEM, (2) a study area polygon, (3) an ocean front line used to determine marine water from estuarine water, and (4) Mean Higher High Water (MHHW) and Highest Astronomical Tide (HAT) height measurements (in meters) for the study area and corrected to NAVD88. The model result is a polygon dataset (feature class in an ArcGIS geodatabase) with attributes for each type of geomorphic feature in the study area.

Table 1. Parameters to classify geomorphic features. Mean Seal Level (MSL), Mean Higher High Water (MHHW), Highest Astronomical Tide (HAT), and Topographic Position Index (TPI).

Feature	Classification Parameters
Intertidal	MSL < elevation < MHHW
Supratidal	MHHW < elevation < HAT
Dune	40 m TPI >= 150, Shape Index < 0.6, hummock intersecting dune dune =
Hummock	12 m TPI >= 50, Shape index > 0.6, Not intersecting a dune
Overwash	200 m TPI > 50
Swale	40 m TPI <= −50, Not intersecting supratidal
Channel	40 m TPI <= −50, Intersecting supratidal
Upland	200 m TPI <= 50

Calculation of the Topographic Position Index (TPI) is a critical component to the model [13,14]. The equation to calculate the TPI is (1):

$$\mathrm{TPI} = ((\mathrm{DEM} - \mathrm{Focal\ Mean}) + (0.5)) \quad (1)$$

For each cell in the DEM, the focal mean was computed and compared to the elevation of the cell. A cell that is higher than its neighboring cells has a positive TPI value, while a cell that is lower than its neighboring cells has a negative TPI. The neighborhood distance for the focal mean depends on the size of the feature. Small features are identified using small neighborhoods, and larger features are identified using larger neighborhoods [14]. Distance sensitivity tests were conducted, and then optimized neighborhood sizes and TPI thresholds were determined for each geomorphic feature. Each TPI calculation has a radius (distance) and number of cells that define the neighborhood around each cell.

The TPI index was scaled to the DEM for each of the study areas and was based on the mean and standard deviation of the focal statistics for each DEM. The scaling enables versatility across study areas so that the model uses the same TPI equations for each type of feature, but also standardizes the index values based on the DEM for each area. The equation to calculate the scaled TPI is (2):

$$\mathrm{TPI\ (scaled)} = \mathrm{int}(((\mathrm{TPI} - \mathrm{mean/stdev}) * 100) + 0.5) \quad (2)$$

The TPI classification identifies topographic peaks and valleys, thus swales and channels were grouped into the same class. These features were then segregated on the basis of their proximity to the supratidal areas. Channels are valleys where water cuts through the barrier island, usually perpendicular to the beach, and these features intersect the supratidal region. Swales are valleys between dunes, usually parallel to the beach, so they are adjacent to dunes and do not intersect the supratidal areas.

Overwash fans are found adjacent to the back barrier. So, the distance between overwash and ocean was calculated, and areas that were greater than 0.5× the standard deviation (stdev) of the distance were classified as overwash, whereas areas closer to the ocean were reclassified as either hummock or dune, depending on the TPI value. Dunes and hummocks have similar TPI values, so a shape index was used to differentiate them. Dunes are generally oval-shaped, while hummocks are circular. The equation to calculate the shape index is (3):

$$\text{Shape Index} = (\sqrt{\text{Area}/\pi})/(\text{Shape Length}/(2 * \pi)) \quad (3)$$

Shape indexes ≤0.6 were classified as dunes, and shape indexes >0.6 were classified as hummocks. Not all dunes are long and linear, so some were misclassified as hummocks. To address this, the distance between dunes and hummocks was calculated, and hummocks that were located closer than 0.5× stdev of the distance to dunes were reclassified as dunes.

The classified maps of each study area were analyzed for change over time. In the northern areas, the time steps were 2001–2005, 2005–2009, 2009–2014, and 2001–2014, and in the southern areas the time steps were 1998–2005, 2005–2010, and 2010–2014. Feature area, elevation, and volume were computed for each time period. Several methods were used to capture feature movements. Oceanfront shoreline dynamics were compared using AMBUR [15]. Dune movement was calculated using Detect Feature Change and Near tools in ArcMap. Change statistics were calculated using polygon overlay, and then cross-tabulation matrices were created. A statistically significant feature change was identified by comparing the expected and observed change [16,17].

3. Results and Discussion

The geomorphic classification model was developed in ESRI's ModelBuilder and run 16 times (four study areas and four dates). The fieldwork GCPs were comparable to the Lidar data and could therefore be used to assess the geomorphology classification results. Overall, the model map accuracy was 76% (Masonboro), 77% (Corolla), 78% (Wrightsville), and 81% (Currituck). Changes were measured using: (1) elevation, volume, area, and percentage of each feature type; (2) shoreline and dune movement; (3) statistically significant changes using cross-correlation matrices. At all four study sites, intertidal and supratidal features had the lowest average elevation, and dunes had the highest average elevation. Most features experienced minimal change in elevation over the time period (1998–2014). Across all study areas, the largest change in volume was from 2005 to 2009/2010.

Upland was the largest feature on Wrightsville and Currituck at 30% of the area and on Corolla upland was 40%. Alternatively, on Masonboro, intertidal and supratidal features were the largest area at ~50% of the island. Changes were less substantial on developed islands in comparison to undeveloped ones. For example, on Masonboro, the largest change was a 17% increase in the supratidal areas from 1998 to 2005, whereas, on Wrightsville, supratidal features increased by 3%. On Masonboro and Wrightsville, from 1998 to 2005, most of the shoreline was eroding. The mean shoreline change was −3.1 m/yr on Masonboro and −0.5 m/yr on Wrightsville, with 72% of the shoreline eroding on Masonboro, and 52% of the shoreline eroding on Wrightsville. Shoreline accretion rates increased, and erosion rates decreased from 2005 to 2010 when the mean shoreline change rate was −1.1 m/yr on Masonboro and +0.5 m/yr on Wrightsville. From 2010 to 2014, the shoreline was again dominated by erosion. In contrast, the northern region was accreting from 2001 to 2005, when the net shoreline change was +0.6 m/yr at Currituck and +0.8 m/yr at Corolla. Currituck had 44% of the shoreline eroding, and Corolla had 22%, resulting in areas of both erosion and accretion. From 2005 to 2009, the majority of the shoreline was accreting, with the mean shoreline change of +1.5 m/yr on Currituck and +2.7 m/yr on Corolla. From 2009 to 2014, almost the whole (more than 90%) shoreline experienced a large amount of erosion, with a mean shoreline change of −3.4 m/yr on Currituck and of −2.7 m/yr on Corolla.

The movement/migration of dune features was calculated by measuring the difference in spatial position through time and was defined as: movement (3 m ≤ distance ≤ 25 m), no change (<3 m), deletion (feature completely eroded), new dune (>25 m). On Masonboro, the largest amount of movement and the creation of new dunes occurred from 2005 to 2010. On Wrightsville, the largest amount of dune movement was from 2010 to 2014, while the largest amount of deletion was from 2005 to 2010. On Currituck, a similar amount of movement occurred from 2001 to 2005 and from 2010 to 2014. The largest amount of deletion was from 2005 to 2009. On Corolla, the largest amount of movement and creation of new features occurred from 2009 to 2014, while the largest amount of deletion was from 2005 to 2009. The mean dune movement ranged from 1.1 m (Masonboro from 2010 to 2014 and Currituck from 2009 to 2014) to 3.9 m (Wrightsville from 2005 to 2010), and the direction was consistently to the southwest.

Polygon overlay and cross-tabular change matrices were generated for each time period. Net gain and loss (in area) were computed per feature type and time period. Significant change was calculated by comparing the observed and expected change [16]. On Masonboro and Wrightsville, the largest significant changes were supratidal and intertidal. Less significant changes occurred in the northern region (Currituck and Corolla), and the most recent time period had the least change.

Regional differences between the north (Currituck and Corolla) and the south (Masonboro and Wrightsville) were much larger than the differences between developed and undeveloped barrier islands. There are two primary reasons why the north is different from the south: geologic setting and beach nourishment. The developed islands had less change and dune movement than the undeveloped islands, because development prevents natural processes such as washover and roll-over. This results in features on the developed islands being "locked" in place, which creates increased shoreline erosion and island narrowing [9].

Storms were a dominant process influencing the four study areas. Post-storm AMBUR analysis computed the average shoreline changes of −3 m/yr (Masonboro), −0.45 m (Wrightsville), −3.4 m/yr (Currituck), and −2.7 m/yr (Corolla). A feature change analysis documented dune erosion and the transition of dunes to supratidal and intertidal and channels. On the undeveloped islands, there was an increase in overwash. In the southern study areas, the stormiest period was from 1998 to 2005, when the area was impacted by eight major storms, four of which were hurricanes. Only a few small storms impacted the northern study areas between 2001 and 2009, and then, in 2011, Hurricane Irene, a category 3 storm, passed directly through the region, likely responsible for the changes observed on Currituck and Corolla.

Beach nourishment temporarily increases the amount of sediment and overall elevation of the oceanfront shoreline (White and Wang, 2003). However, nourishment has been shown to result in the largest amount of storm-induced erosion [11]. Beach nourishment took place at Masonboro and Wrightsville in 2006 and 2010, just prior to the Lidar data collection. Shorelines accreted from 2005 to 2010 with an average shoreline change rate of +1.2 m/yr at Masonboro and +0.5 m/yr at Wrightsville. This accretion was followed by a period of high erosion from 2010 to 2014: −1.7 m/yr at Masonboro and −3.5 m/yr at Wrightsville. The location of accretion corresponded to the areas of highest erosion.

4. Conclusions

One of the benefits of using Lidar data for studying coastal systems is that it provides elevation; therefore, in sandy coastal environments, where many different features have similar reflectance properties, features can be distinguished on the basis of topography [18]. This study developed an automated model to classify barrier island geomorphic features. On average, the model accuracy was 80%, which is acceptable given that it can be difficult to precisely measure the boundaries of different types of features that gently vary over the terrain. Historical Lidar can be used to analyze change through time, and geospatial techniques can measure the distance and direction that features have moved. The model was tested at undeveloped and developed islands and islands with different geologic settings. When storms occur, they are the dominant force influencing change. Between stormy periods, other activities, such as beach nourishment, can temporarily increase the oceanfront elevation, which later leads to the greatest rates of erosion. Lastly, urban development reduces the amount of change because natural processes are prohibited from moving dunes and adjacent areas.

Author Contributions: J.N.H. conceived and designed the research, and M.A.F. conducted fieldwork, edited and developed the model, and generated the numerical results. J.N.H. and A.D.H. analyzed the data, and all three authors contributed to writing the paper.

Acknowledgments: The authors would like to thank the United States Army for funding Maria Frishman for her MS in the Geoscience program and the Geological Society of America for funding fieldwork. Timothy Moss assisted with TPI and Shape Index testing and model development, and Michael Okely, Yvonne Marsan, and Kevin Carver assisted with fieldwork.

Conflicts of Interest: The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

References

1. Paris, P.; Mitasova, H. Barrier island dynamics using mass center analysis: A new way to detect and track large-scale change *ISPRS Int. J. Geo-Inf.* **2014**, *3*, 49–65.
2. White, S.A.; Wang, Y. Utilizing DEMs derived from LIDAR data to analyze morphologic change in the North Carolina coastline: *Remote Sens. Environ.* **2003**, *85*, 39–47.
3. FitzGerald, D.M., Fenster, M.S., Argow, B.A.; Buynevich, I.V. Coastal impacts due to sea level rise. *Annu. Rev. Earth Planet. Sci.* **2008**, *36*, 601–647.
4. Judge, E.K.; Overton, M.F. Remote sensing of barrier island morphology: Evaluation of photogrammetry-derived digital terrain models. *J. Coast. Res.* **2001**, *17*, 207–220.
5. Sallenger, A.H.; Krabill, W.B.; Swift, R.N.; Brock, J.; List, J.; Hansen, M.; Holman, R.A.; Manizade, S.; Sontag, J.; Meredith, A.; et al. Evaluation of airborne topographic lidar for quantifying beach changes. *J. Coast. Res.* **2003**, *19*, 125–133.
6. Smith, C.G., Culver, S.J., Riggs, S.R., Ames, D.; Corbett, D.R.; Mallinson, D. Geospatial analysis of barrier island width of two segments of the Outer Banks, North Carolina, USA. Anthropogenic curtailment of natural self-sustaining processes. *J. Coast. Res.* **2008**, *24*, 70–83.
7. Mitasova, H.; Overton, M.F.; Recalde, J.J.; Bernstein, D.J.; Freeman, C.W. Raster-based analysis of coastal terrain dynamics from multitemporal Lidar data. *J. Coast. Res.* **2009**, *25*, 507–514.
8. Allen, T.R.; Oertel, G.F.; Gares, P.A. Mapping coastal morphodynamics with geospatial techniques, Cape Henry, Virginia, USA. *Geomorphology* **2012**, *137*, 138–149.
9. Riggs, S.R., Ames, D.V.; Culver, S.J.; Mallinson, D.J. *The Battle for North Carolina's Coast: Evolutionary History, Present Crisis, and Vision for the Future*; The University of North Carolina Press: Chapel Hill, NC, USA, 2011; p. 142.
10. Woolard, J.W.; Colby, J.D. Spatial characterization, resolution and volumetric change of coastal dunes using airborne LiDAR: Cape Hatteras, North Carolina. *Geomorphology* **2002**, *48*, 269–287.
11. Gares, P.; Wang, Y.; White, S. Using LiDAR to monitor a beach nourishment project at Wrightsville Beach, North Carolina, USA. *J. Coast. Res.* **2006**, *22*, 1206–1219.
12. Houser, C.; Hapke, C.; Hamilton, S. Controls on coastal dune morphology, shoreline erosion and barrier island response to extreme storms. *Geomorphology* **2008**, *10*, 223–240.
13. Weiss, A. Topographic position and landforms analysis. In Proceedings of the ESRI User Conference, San Diego, CA, USA, 3–13 July 2001; pp. 200–200. Available online at: http://www.jennessent.com/downloads/TPI-poster-TNC_18x22.pdf (accessed on 21 February 2015).
14. Reu, J.D.; Bourgeois J.; Bats, M.; Zwertvaegher, A.; Gelorini, V.; DeSmedt, P.; Chu, W.; Antrop, M.; DeMaeyer, P.; Finke, P.; et al. Application of the topographic position index to heterogeneous landscapes. *Geomorphology* **2013**, *186*, 39–49.
15. Jackson, C.W.; Alexander, C.R.; Bush, D.M. Application of the AMBUR R package for spatio-temporal analysis of shoreline change: Jekyll Island, Georgia, USA. *Comput. Geosci.* **2012**, *41*, 199–207.
16. Pontius, R.G.; Shusas, E.; McCachern, M. Detecting important categorical land changes while accounting for persistence. *Agric. Ecosyst. Environ.* **2004**, *101*, 251–268.

17. Halls, J.N. Measuring habitat changes in barrier island marshes: An example from southeastern North Carolina, USA. In *Remote Sensing and Geospatial Technologies for Coastal Ecosystem Assessment and Management*; Yang, X., Ed.; Springer-Verlag: Berlin, Germany, 2009; pp. 391–413.
18. Victor, K. Beach profiling and LiDAR bathymetry: An overview with case studies. *J. Coast. Res.* **2011**, *27*, 1019–1028.