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Monitoring Sediment Dynamics and Vegetation Competition Based on Micro-Topography and Terrestrial LiDAR for Wetland Restoration

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MONITORING SEDIMENT DYNAMICS AND VEGETATION COMPETITION
BASED ON MICRO-TOPOGRAPHY AND TERRESTRIAL LIDAR
FOR WETLAND RESTORATION

A Dissertation

Submitted to the Graduate Faculty of the
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in

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by

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Abstract

With the ability to attenuate wave and limit erosion, coastal wetlands are important to protect shoreline for coastal communities. Micro-topography in coastal wetlands has a significant influence on hydrology, habitat variability and ecosystem functions. However, when mapping micro-topography by terrestrial LiDAR in coastal environments, the coverage of dense vegetation leads to a relatively low chance of laser penetration through the canopy to the ground. This dissertation proposes a rapid and flexible terrain mapping solution for the densely vegetated coastal environment by integrating crown structure from terrestrial LiDAR with terrain samples from GPS. The validated results in the study site demonstrate that the proposed method successfully corrected the terrain in low and tall vegetation.

Based on the accurate micro-topography mapping, this dissertation used an object-oriented tool, Coastal Morphology Analyst (CMA), to examine sediment change patterns for the study site. The CMA analysis identified depositional and erosional objects successfully, which are the useful data source for coastal wetland restoration and essential data input for vegetation pattern analysis.

The micro-topographic derived variables slope and Topographic Wetness Index (TWI) were generated to analyze the influence of micro-topography on sediment change and vegetation patterns. The single variable slope cannot separate erosion and deposition efficiently, but the single variable TWI is capable of separating at least 75% of the erosional and depositional objects. The erosion is more likely to occur at the place with small TWI. When integrating the class change type, TWI is a better variable to predict the erosional area for bank nourishment to improve wetland engineering.
The class change between 2015 and 2016 was calculated by subtracting the classification of 2015 from 2016. For low vegetation, 69% of the areas converted to tall vegetation and 30% of the areas remained low vegetation. For tall vegetation, 98% of the areas remained tall vegetation and only 2% of the areas converted to low vegetation. Therefore, more low vegetation converted to tall vegetation from 2015 to 2016. For bare ground, 77% and 13% of the areas converted to tall and low vegetation respectively, while only 10% of the areas remained bare ground. For the wetland restoration in the area with the similar environmental condition, Spartina alterniflora is a preferred choice for planting.
Chapter 1. Introduction

More than one third of the world’s population lives in coastal areas and small islands (Brown, UNEP et al. 2006), but coastal communities suffer serious threats from the sea that result in damage to human property and loss of life (Gedan, Kirwan et al. 2011). With the ability to attenuate wave and limit erosion, coastal wetlands are important to protect shoreline for coastal communities. Beyond the shoreline protection, coastal wetlands provide other services for coastal communities, such as maintaining habitats for wildlife, supporting commercial fisheries and providing recreational opportunities (United States Environmental Protection Agency 2018). However, the coastal wetland in the world lost more than 50% of its area in the 20th century (Li, Bellerby et al. 2018).

As a state comprising about 40% of the U.S. continental wetlands, Louisiana has lost 5000 km² of coastal wetlands over the past decades (Jankowski, Tornqvist et al. 2017). If the current land loss rates continue unabated, Louisiana will lose more than one million acres of coastal wetlands by the year 2040, which is larger than the state of Rhode Island (Watzin, Gosselink et al. 1992). While facing severe coastal wetlands loss, Louisiana has taken multiple measures to protect and restore wetlands. Among these wetland restoration solutions, constructing vegetated barrier is a cost-effective and scalable solution for shoreline protection and bank stabilization. After the construction of the vegetated barrier, the wetlands inside are protected from erosion and will regrow into clusters. However, there is a lack of quantitative assessment of effectiveness and sustainability of these wetland-engineering projects in practice.

Two major indexes for assessment are status of sediment change measured through topography and vegetation spatial patterns. Topography acts upon the resources needed for plant existence, shaping exogenous disturbance patterns, and modulating biotic interactions such as
competition. Therefore, topography is an important factor for local plant diversity patterns across most habitats (Moeslund, Arge et al. 2013). Increasingly accurate topographic dataset is required in coastal morphology to perform reliable simulation of coastal erosion, flooding phenomena and assessment of the coastal sediment budget (Mancini, Dubbini et al. 2013). While some applications utilize existing historical data, the ever-changing landscapes of the coastal fronts, the terrain mapping difficulty due to dense vegetation, and the intense water level and tide changes makes accurate topographic mapping challenging in coastal environments. In addition, many morphological studies require timely surveys at critical stages before and after an event. Timely mapping and assessment of topographic changes are therefore critical for coastal morphological analysis.

Elevation profiles, measured by total station, leveling instrument, and GPS surveys in representative locations, are commonly used for coastal topographic mapping and analysis. However, considering the spatial heterogeneity of coastal lands and hydrodynamics, analysis based on a limited number of profiles may be insufficient for accurate survey of morphological changes over the large area (Palmsten and Holman 2012). Higher accuracy often requires a larger array of sensors or more measurements (Erikson and Hanson 2005), which can be challenging and costly in field environments using these discrete measurement methods.

In recent decades with advanced remote sensing developments, various remotely sensed data have played an essential role in mapping and modelling coastal morphology (Zhao, Bai et al. 2016). Satellite images, such as Landsat TM images, are widely applied in coastal morphological researches (Jangir, Satyanarayana et al. 2016), but they are restricted to large-scale study because of the relatively low spatial and temporal resolution. Additionally, other remote sensed methods like photogrammetric stereo mapping (Palmsten and Holman 2012), radar (Dixon, Amelung et al.
and LIght Detection And Ranging (LiDAR) (Houser, Hapke et al. 2008) have been used for 3-D coastal morphological analysis and demonstrated superior advantages over traditional methods. Especially, recent developments of portable surveying techniques such as terrestrial LiDAR and unmanned aerial vehicle (UAV) have started filling the gap between traditional remotely sensed images (satellite and aerial images with limited time, resolution, and coverage) and tedious point-based field survey (e.g., GPS, levelling instrument, and total station). Terrestrial LiDAR has demonstrated significant advantages for quick and accurate 3D topographical mapping. It is commonly used as in situ high-resolution mapping tools integrated with other field data for interdisciplinary studies. In addition, it provides a rapid and timely surveying solution for areas or events that are lack of historical data.

Micro-topographic variability has traditionally been measured by relative elevation of the soil surface over a specified distance (length scale) and/or time interval (Sankey, Ravi et al. 2012). Terrestrial LiDAR system coupled with high-precision GPS provides a reliable solution for mapping coastal micro-topography. Previous studies have derived micro-topographic variability from measurements of the variance in LiDAR point elevations (Haubrock, Kuhnert et al. 2009; Eitel, Williams et al. 2011; Sankey, Eitel et al. 2011). Micro-topography in coastal wetlands has significant influence on hydrology, habitat variability, and ecosystem functions (Pollock, Naiman et al. 1998; Moser, Ahn et al. 2007; Moser, Ahn et al. 2009). Therefore, micro-topography is a useful data source for coastal wetlands studies.

Correct mapping of topography is critical for successive definition of aboveground elements such as vegetation. With high-accuracy scanning technology, terrestrial LiDAR is also widely applied in mapping and quantifying vegetation, but most applications focus on forest with sparse ground covering. Some coastal areas like coastal wetlands are always covered with dense
vegetation, which can affect the accuracy of topographical mapping seriously. Because of the poor penetration of laser signal through dense vegetation, measuring micro-topography by terrestrial LiDAR under densely vegetated coastal environments is challenging (Karstens, Jurasinski et al. 2016). Nevertheless, how terrestrial LiDAR response in the densely vegetated coastal environment has not been explored in deep.

The focus of this dissertation is to explore the application of terrestrial LiDAR in mapping micro-topography in densely vegetated coastal environments and analyse the influence of micro-topography on spatial patterns of vegetation. This research aims at:

- experimenting terrestrial LiDAR for micro-topography mapping in densely vegetated coastal environments and assessing the uncertainties caused by different vegetation based on existing terrain mapping method;
- developing a new local-adaptive terrain correction method by integrating crown structures from terrestrial LiDAR with limited ground samples from GPS for a portable, flexible, and rapid mapping solution for densely vegetation environments;
- applying the improved terrain correction method for multi-temporal monitoring of a wetland restoration project and quantitatively assessing sediment erosion and deposition and land cover changes;
- exploring the colonization and competition processes of different planted vegetation species to improve wetland engineering.

The remainder of the dissertation is structured as follows. Chapter 2 is the review of the literature for the research. Chapter 3 introduces the study site and field data collection. The study site is located at the Buras Boat Harbor, Plaquemines Parish, Louisiana, and a representative location with severe wetland loss in the birds-foot-delta of the Mississippi River. The field data
collection includes the terrestrial LiDAR scanning and GPS surveying on July 30, 2014, October 1, 2015, and October 29, 2016 respectively. Chapter 4 examines the accuracies of micro-topography mapping in densely vegetated coastal environments by terrestrial LiDAR and proposes an improved adaptive method for terrain correction. Chapter 5 detects the yearly sediment erosion and deposition based on the micro-topography mapping from chapter 4. Before the application of an object-oriented sediment change analysis for the study site from 2014 to 2016, the method is validated in an indoor experiment. Chapter 6 extracts the spatial distribution of vegetation from dense LiDAR data and explores correlation between micro-topography and vegetation distribution for wetland restoration projects. Chapter 7 summarizes the results and conclusions from the preceding chapters and discusses future work.
Chapter 2. Literature Review

Coastal zones are among the most productive ecosystems (Baztan, Chouinard et al. 2015) while being the most densely populated areas in the world with fast population growth rates (Nicholls, Wong et al. 2007; Neumann, Vafeidis et al. 2015). However, the various threats of natural impacts, such as rising sea levels, land subsidence and hazards (floods, storm surges, hurricanes, earthquakes, salt water intrusion etc.), as well as disturbances from anthropogenic activities have significantly altered coastal morphology and landscapes (Nicholls, Wong et al. 2007; Baztan, Chouinard et al. 2015; Neumann, Vafeidis et al. 2015). Coastal morphology focuses on the status and change of coastal features such as sediment and vegetation, which are critical to help understanding and solving various coastal issues (Samaras and Koutitas 2012).

Existing methods for coastal morphological mapping and analysis are usually based on GPS, photogrammetric stereo mapping (Holland, Puleo et al. 2001; Palmsten and Holman 2012), radar (Dixon, Amelung et al. 2006), LIght Detection And Ranging (LiDAR) (Houser, Hapke et al. 2008), and elevation profiles (Morton, Leach et al. 1993). Elevation profiles through samples in representative locations are common field-based methods to quantify coastal morphology. For example, Masselink and Pattiaratchi (2001) conducted weekly or bi-weekly beach morphology monitor at five beach locations with one elevation profile surveyed in two beaches and three profiles in the other three beaches. This type of sparsely distributed profile analysis is simple and effective but the interpretive results may change with sample locations as morphological characteristics and hydrodynamics may vary with land orientation, wind direction, vegetation cover, sediment types etc. To minimize this bias, Dail, Merrifield et al. (2000) applied dense point surveys using RTK GPS to model coastal morphology through interpolating methods. However, this approach is labor intensive and challenging for large area applications.
In recent decades with advanced remote sensor developments, growing number of studies have applied photogrammetric stereo mapping, radar and LiDAR data for 3-D coastal morphological analysis and demonstrated superior advantages over traditional methods. Palmsten and Holman (2012) monitored sediment dynamics in a wave tank by multi-temporal photogrammetric stereo mappings. The results were compared to 16 traditional profile surveys based on a laser range finder and an acoustic sensor, and showed an average root mean square error (RMSE) of 0.05 m. The research demonstrated advantages of photogrammetric stereo mapping with high spatial resolution (~0.05 m), high temporal resolution (15 minutes), and non-intrusive measurement approach. Dixon, Amelung et al. (2006) mapped the spatial distribution and assessed the rate of land subsidence in New Orleans over the three years before Hurricane Katrina using RADARSAT. Houser, Hapke et al. (2008) used airborne LiDAR data before and after Hurricane Ivan to study the impact of a hurricane event on morphological changes of beach dunes.

Among the new remote sensing technologies, terrestrial LiDAR and UAV have demonstrated significant advantages for quick and accurate 3D topographical mapping. Terrestrial LiDAR has been applied in various field applications because of its high precision and high resolution (Meng, Wang et al. 2009; Meng, Wang et al. 2009; Zhao, García et al. 2015). Kennedy, Ierodiaconou et al. (2014) integrated terrestrial LiDAR with multi-beam sonar to map coastal morphology with mostly granitic surfaces. They used surface texture, roughness, and elevation profiles to identify geological features, illustrate landscape evolution and analyze morphological patterns. With the advantage of flexible mounting locations, UAV has demonstrated its popularity in cost-effective mapping and rapid response to events (Stefanik, Gassaway et al. 2011; Turner, Lucieer et al. 2012; Klemas 2015). Mancini, Dubbini et al. (2013) applied stereo mapping method
on an unmanned aerial vehicle (UAV) platform and proved its effectiveness in coastal morphological mapping. Breckenridge and Dakins (2011) estimated percentage ground cover through a gridded manual system based on selected near-nadir UAV images and compared the results with field measurements. Turner, Lucieer et al. (2012) applied the Structure from Motion (SfM) technology to produce georectified orthophotos from UAV flights. Compared with the traditional photogrammetric methods based on accurately measured camera positions and orientations, SfM is a relatively new technology developed in the computer vision field that is based on region detector. It is robust to camera positions and angles of acquired images. As a result, SfM simplified the process in converting raw UAV images to 3D topographic mapping products, which has promoted the application of UAV in various environments (Watts, Ambrosia et al. 2012; Mathews and Jensen 2013; Jensen and Mathews 2016).

In coastal environments where storm surges, hurricanes and floods frequently disturb coastal lines, dense vegetation commonly present to help stabilizing sediment and preventing land loss. Large areas of dense vegetation, such as marshes, are often planted to protect from shoreline erosion for coastal wetlands restoration. The coverage of dense vegetation leads to a relatively low chance of laser penetration through the canopy to the ground. In addition, bare ground is hardly found in this coastal environment, so the method of interpolation is not effective for topographic mapping. Previous studies have shown that vegetation such as trees, shrubs, and grasses can cause significant errors in terrain mapping (Su and Bork 2006; Heritage and Hetherington 2007; Meng, Wang et al. 2009; Meng, Currit et al. 2010) that lead to error propagation in the following sediment dynamics and morphological change analysis (Hebeler and Purves 2009; Hutton and Brazier 2012). For example, Hutton and Brazier (2012) examined the impact of uncertainty in SRTM (90 m resolution for global and 30 m for the United States) on topographic indices and found significant
impacts on watershed scale analysis. Others have studied the error propagation into aboveground biomass (Chen, Vaglio Laurin et al. 2015), plant growth (Hopkinson, Chasmer et al. 2008), and carbon estimation (Mascaro, Detto et al. 2011) etc. Relatively more studies examined the impact of airborne LiDAR sampling and interpolation methods on DTM generation (Chu, Chen et al. 2014; Chen, Vaglio Laurin et al. 2015).

Recent development of terrestrial LiDAR system provides a rapid and effective approach to map coastal micro-topography. However, high uncertainty under dense vegetation remains a significant challenge due to inability of signal to penetrate tall and dense vegetation. Coveney and Fotheringham (2011) explored the terrestrial laser scan error in the presence of dense ground vegetation and clarified the component contributions to elevation error deriving from vegetation occlusion, scan co-registration error, point-cloud geo-referencing error and target position definition. The results showed relatively significant impact from vegetation occlusion. Fan, Powrie et al. (2014) applied local-highest-point and local-lowest-point filters to derive vegetation height and vegetation-induced elevation error based on terrestrial LiDAR, respectively. The results showed that various factors such as the vegetation height and density, scan distance, scan resolution and incidence angle contributed to the error of terrain estimation in vegetated areas.

Large errors of terrain estimation by terrestrial LiDAR in vegetated areas generally lead to an unreliable micro-topography mapping. Low-accuracy micro-topography mapping cannot be input for the future morphological analysis, so the results derived from terrestrial LiDAR in vegetated environments need further corrections for quality micro-topography mapping. Guarnieri, Vettore et al. (2009) presented a novel filter scheme for Terrestrial LiDAR point cloud filtering integrated with GPS survey points to define ground points within low and dense vegetation. They separated ground points from vegetation based on the GPS survey points and refined the
classification results for dense and sparse vegetation considering the reflectance of laser return intensity. The approach was applied in a tidal marsh environment with continuous vegetation over a gentle slope and the result is reasonable. Rodriguez-Caballero, Afana et al. (2016) improved this method by adapting the window size according to different types and sizes of plants. The accuracy of the final DTMs was improved by ~30% under dense canopy plants and over ~40% on the open spaces between plants. Che and Olsen (2017) proposed a fast ground filtering for terrestrial LiDAR data via Scanline Density Analysis. They first separated the ground points, density features and unidentified points based on an analysis of point density within each scanline. Then they clustered the ground candidates by region growth and further refined the ground points. The approach shows effectiveness and robustness with datasets from both urban and natural environment. Researchers have improved the micro-topography mapping by filtering or terrain correction, but most of them focus on sparse or short dense vegetation environments. Few researches have addressed with dense vegetated coastal environments.
Chapter 3. Study Site and Field Data Collection

As a state accounting for 80% of the wetland loss in the United States (Theriot 2014), Louisiana is experiencing the fast wetland loss due to combined factors including salt water intrusion, natural hazards, and anthropogenic activities such as forest logging, fishing, oil and gas extraction, and reduction of sediment (Pendarvis 2010). Wetland restorations through dredging and reconstruction of artificial berms and coastal barriers are frequently used methods. However, these projects are expensive and subject to the need of frequent nourishment due to severe weather, wave and inundation. Therefore, timely mapping and assessing coastal morphological changes before and after construction events are critical for understanding the dynamics between sediment change and hydrological processes and evaluating the sustainability of restoration efforts.

The study site is located at the Buras Boat Harbor, Plaquemines Parish, Louisiana (Fig.1), a representative location with severe wetland loss in the birds-foot-delta of the Mississippi River. In order to alleviate the wetland loss in the parish, the government has conducted many wetland restoration projects using various technologies including the three reconstructed earthen berms with planted vegetation on the ocean side in August 2014 in this study site (Fig. 1d).

This study site covers the west segment of the berms that is about 380 m long and 25 m wide oriented in W-E direction with three rolls of Chrysopogon zizanioides (Vetiver Grass), Panicum vaginatum Sw (Seashore Paspalum) and salt-tolerant Spartina alterniflora planted from the center of the berm to the edge. After one year of construction, tall and dense Spartina alterniflora colonized the edge of the berm, and low and dense Panicum vaginatum Sw covered the areas with relatively high elevation while Chrysopogon zizanioides barely survived. I mapped the berm on July 30, 2014, October 1, 2015, and October 29, 2016 to monitor the restoration
progress. This research applied Terrestrial LiDAR in all three mappings for change analysis. Additionally, RTK GPS was surveyed for terrain correction and accuracy assessment.

Figure 1. Study site at the Buras boat harbor, Plaquemines Parish, Louisiana. The images in (b) and (c) are aerial photographs from the USGS website and demonstrate the wetland degradation phenomena from 1998 to 2013. The 2015 Google Earth image (d) shows the landscape after berm construction. (e) is the orthophoto from UAV data collected on 1 October 2015.

The terrestrial LiDAR system used in this study is RIEGL VZ-1000 with a range measurement precision of 5 mm and an accuracy of 8 mm for a 100 m range. It provides high-density measurement capability up to 122,000 measurements/second, a 360° horizontal and 100° vertical field of view and a scanning range of 1400 m. An RTK GPS model of Trimble R10 with centimeter level measurement accuracy was integrated with the terrestrial LiDAR to improve the localization accuracy. Figure 2 demonstrates the terrestrial LiDAR system.
Figure 2. Terrestrial LiDAR system

Trimble R10 GPS
Nikon D800 Camera
Riegl VZ 1000 Laser Scanner
Kestrel Weather Meter
Field Laptop for Data Collection
Chapter 4. Mapping Micro-Topography in Densely Vegetated Coastal Environments Using Terrestrial LiDAR

4.1 Introduction

In recent decades, LiDAR has become a popular and reliable data source for coastal morphological studies. Through tracking the time where a pulse occurred in a laser beam as triggered by an object, LiDAR technology is able to measure the location of the object and hence produces dense point clouds with x, y, and z coordinates for objects on or above ground surface. Typical platforms for LiDAR sensors include airborne, mobile, UAV, and terrestrial system with either green or near-infrared wavelengths. Terrestrial LiDAR, also called terrestrial laser scanner, is a portable surveying system mounted on a tripod and can rotate 360 degrees to acquire virtual reality-like color-coded dense point clouds of the surrounding environment. Through positioning the scanner at multiple locations and multi-station registration, the system can extend to large area mapping. In addition, LiDAR technology is well known for producing multiple layers in vegetated areas and provides advantages in characterizing vertical structures of vegetation. These unique characteristics make terrestrial LiDAR system a suitable solution to monitor coastal morphological changes and vegetation dynamics and a quick-response surveying tool for wetland restoration to document landscapes at critical stages such as before and after wetland restoration or a disturbance (e.g., floods, storm surges, and hurricanes), and seasonal or annual surveys.

However, high uncertainty of mapping under dense vegetation remains a significant challenge due to inability to penetrate tall and dense vegetation of coastal environments. This study aims to apply terrestrial LiDAR to map micro-topography of a sand berm reconstructed through a coastal wetland restoration project and quantify the impact of dense vegetation on the uncertainty of morphological modeling to evaluate whether further correction is necessary. To minimize the
potential uncertainty, this study presents a novel solution to correct it by integrating crown structure from terrestrial LiDAR with terrain samples from GPS.

4.2 An Adaptive Method for Terrain Correction

4.2.1 Overview of the Method

This chapter presents a local-adaptive method to assign terrain correction factors in densely vegetated environments based on crown structure obtained from terrestrial LiDAR and vegetation types from object-oriented classification and terrain samples from GNSS data. The conceptual workflow includes three main stages as illustrated in Figure 3. Stage 1 conducts terrestrial LiDAR scanning and generates initial DTM by multi-station registration, noise removal, site clip, and an iterative ground filtering process. Stage 2 applies object-oriented classification based on the statistical raster layers produced from interpolation and statistical resampling of LiDAR point cloud and compares it with pixel-based classification. Stage 3 corrects terrain for low vegetation and tall vegetation areas based on the classification results of stage 2. In order to correct terrain, the correction factor 95th percentile of errors is assigned to the DSM in low vegetation area, and the regression-based adjusted correction factor is assigned to the DTM in tall vegetation area. The following sections illustrate and validate the application of this method through a densely vegetated coastal wetland restoration site.
4.2.2 Stage 1: Initial DTM Generation from Terrestrial LiDAR Data

In this study, the processing of the collected terrestrial LiDAR data was performed through the software RiSCAN PRO, which is the companion software for RIEGL terrestrial LiDAR systems. A single scan results in millions of data points with X, Y, Z coordinates and the point cloud can be viewed in 2D or 3D with color-coding by scanning range and point intensity to enhance the studied objects. After collecting all the terrestrial LiDAR data from field, the first step
of processing was to register all scan positions together through multi-station registration to the NAD 1983 Louisiana South Plane coordinate system. In this step, the performance of registration was dependent on the accuracy of the GNSS associated with the terrestrial LiDAR and targets. Integrated with Louisiana State University’s C4G real-time network, the GNSS provided the ability to obtain highly accurate positions. Then the second step was to remove noisy points manually and cut the whole dataset into the designated study site area. In this step, because of the huge data size, the noise removal was processed for each scan respectively instead of the whole dataset. All the clean data was merged together for next step processing.

The derived raw LiDAR point clouds from the multi-station scanning of typical coastal landscapes is a mixture of measurements from ground, marshes, birds, boats, and man-made facilities such as floating buoys, buildings, and other harbor infrastructures (Meng, Wang et al. 2009; Meng, Currit et al. 2010; Zhao, Garcia et al. 2015). In order to generate DTM from these dense point surveys, points reflected from ground surface need to be filtered first and then interpolated into 3-D terrain models of the terrain (Meng, Currit et al. 2012). Based on the results from the first two steps, an iterative process was applied, which was a combined function including filter, triangulation and separation, to generate points clouds for DTM. Then the point clouds were exported into ArcGIS to generate an initial raster DTM. This research applied a local-lowest-point filter to generate DTM with a resolution of 6 cm based on the average point density.

After the data processing in RiSCAN PRO, the resulted point cloud was imported into ArcGIS and interpolated into DTM with the resolution of 6 cm. As the process of interpolation generated artificial surface in blank areas near the edge of the berm due to lack of points in water, I delineated the berm according to the data coverage from the point cloud and cutted the initial DTM to the delineated berm shape as shown in Figure 4.
The elevation range of the initial DTM is 4.07 m, which is much higher than reality. This is due to overestimation caused by the blockage of laser signal in the vegetated areas, especially in areas with tall vegetation. The signal cannot travel through the dense vegetation to hit the ground, leading to a relatively higher elevation value than actual ground surface. Due to the signal blocking by dense vegetation, the accuracy of the generated DTM is uncertain and it is necessary to conduct accuracy assessment to evaluate the reliability of terrain mapping results and compare the accuracies before and after terrain correction. Therefore, a set of GNSS recordings were separately selected for bare ground, tall vegetation, and low vegetation along evenly distributed transects. As a result, 56 points on bare ground, 61 points on low vegetation and 55 points on tall vegetation were selected respectively. These three sets of samples surveyed through GNSS receiver have an RMS of 0.016 m for horizontal accuracy and an RMS of 0.022 m for vertical accuracy.
Table 1 shows the results of accuracy assessment, where positive values indicate overestimation of elevation values. For bare ground area, the mean error and standard deviation is -0.003 m and 0.023 m respectively, demonstrating that the terrestrial LiDAR is capable of generating a reliable and accurate DTM without the influence of vegetation. Therefore, the DTM correction is not necessary for the bare ground areas. However, the mean errors in the low and tall vegetation are 0.377 m and 0.993 m respectively, which causes significant errors for subsequent morphological analysis. Therefore, DTM correction is necessary and critical for densely vegetated coastal environments.

Table 1. Accuracy assessment of initial DTM generated from terrestrial LiDAR

<table>
<thead>
<tr>
<th>Land Cover</th>
<th>Minimum (m)</th>
<th>Maximum (m)</th>
<th>Mean (m)</th>
<th>Standard Deviation (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bare ground</td>
<td>-0.067</td>
<td>0.091</td>
<td>-0.003</td>
<td>0.023</td>
</tr>
<tr>
<td>Low vegetation</td>
<td>-0.050</td>
<td>0.573</td>
<td>0.377</td>
<td>0.125</td>
</tr>
<tr>
<td>Tall vegetation</td>
<td>0.043</td>
<td>1.783</td>
<td>0.993</td>
<td>0.397</td>
</tr>
</tbody>
</table>

4.2.3 Stage 2: Object-Oriented Classification

When applying terrestrial LiDAR in the coastal environment, laser signal can hardly hit the ground by penetrating through the dense vegetation. Our previous study showed that ground filtering is problematic in areas with steep slope and dense or low vegetation [11]. Therefore, potential problematic areas in this study site may occur in the area densely covered by tall and short vegetation. For example, one year after the berm construction, tall smooth cordgrass densely covered most areas along both sides of the sand berm, while seashore paspalum dominated mostly middle to center part of the berm at higher elevation. Few other species originated from local soil and grew in a relatively fewer population after the first year of berm construction. The vegetation
can cause different level of uncertainty in the morphological modeling and hence should be quantified and corrected if possible.

The vegetation with different character, such as height, density, etc., makes different impact on signal transmitting. Therefore, DTM correction based on land cover classification is approachable and this has been proved by previous researches. Hladik, Schalles et al. (2013) conducted a successful terrain correction in a saltmarsh by integrating airborne LiDAR data from a winter season with hyperspectral images. They combined the classification with the LiDAR-derived Digital Elevation Model (DEM) to correct elevation errors and reduced DEM overall mean error and RMSE. McClure, Liu et al. (2016) applied correction factors to corresponding vegetation species and improved the vertical accuracy of a 1 m LiDAR–derived DEM using a RTK GPS dataset and local vegetation data within a tidal salt marsh.

In this study, the point cloud generated from the terrestrial LiDAR data was imported into ArcGIS 10.3 and interpolated into rasters. As a result, four rasters were derived from the interpolation, including maximum height, minimum height, mean height and height difference. The resolution of these rasters was consistent with that of the initial DTM as 6 cm. All 4 rasters were imported into eCognition to conduct the object-oriented classification. As two main types of vegetation spreaded on the berm, I can classify the whole study site into three classes: tall vegetation dominated by smooth cordgrass, low vegetation dominated by seashore paspalum, and other bare ground areas. Object-oriented classification is based on the information from a set of similar pixels called image objects and it outperforms pixel-based classification in some cases for classification of high-resolution images (Gao, Mas et al. 2006; Yu, Gong et al. 2006; Platt and Rapoza 2008; Myint, Gober et al. 2011; Duro, Franklin et al. 2012). In order to compare it with pixel-based classification, a supervised classification using support vector machine (SVM)
classifier was conducted. SVM has been proven robust and reliable methods that have been validated in many studies (Pal and Mather 2005; Liu, Jing et al. 2013; Niu and Ban 2013; Zhang and Xie 2014).

The object-oriented classification was conducted and the accuracy was assessed and compared with pixel-based classification. The first step of the object-oriented classification is a segmentation of the image, which produces image objects based on their spectral and textural characteristics. In this process, I used the algorithm of multi-resolution segmentation and spectral difference segmentation by equally weighting of all 4 rasters. The scale parameter was set to 10 and for the composition of homogeneity criterion, the value of shape was set to 0.6 and the value of compactness was set to 0.5. After the segmentation, a classification based on thresholds was applied for bare ground. Training samples were selected randomly on the remaining unclassified objects for tall vegetation and low vegetation. Finally, based on these selected samples, a nearest neighbor classification was conducted. For pixel-based classification, a set of polygons (about 100 pixels each polygon) were selected on the berm randomly as training samples for SVM classifier.

To compare these two classification methods, I performed the accuracy assessment for classification using 47 samples for bare ground, 47 samples for low vegetation and 56 samples for tall vegetation (Figure 5). The overall accuracies were 92.7% and 82.0% for object-oriented and pixel-based classification respectively, with kappa statistics of 0.89 and 0.73. For object-oriented classification and pixel-based classification, user’s accuracy of individual classes ranged from 88.9% to 95.8% and from 60.8% to 97.9%, and producer’s accuracy ranged from 88.9% to 96.9% and from 74.6% to 88.2% respectively. The accuracy assessment proved that the object-oriented method yielded a better classification result with a higher overall accuracy and Kappa value. Both classification images are shown as in Figure 6 and Figure 7.
Figure 5. Samples distribution for accuracy assessment of classification

Figure 6. Classification result based on object-oriented Method
4.2.4 Stage 3: Terrain Correction

*DTM Correction for Tall Vegetation*

DTM correction is necessary for those areas covered by tall and dense vegetation due to the block of laser signal. Filtering has been proved as an efficient method to generate DTM in vegetated areas (Streutker and Glenn 2006; Wang, Menenti et al. 2009; Rodriguez-Caballero, Afana et al. 2016). The filtering window can be adjusted to the terrain complexity so that signal can hit ground. However, adjusting window size is ineffective in large areas of dense vegetation due to lack of nearby ground such as the study site in this research, resulting in significant overestimation of terrain. These errors need correction for all subsequent usage.

The density of the smooth cordgrass is high, but their heights are relatively consistent. Correction factor can be applied to this kind of vegetation to improve the DTM. However, in this case, the height of the smooth cordgrass is around 2 m, which is higher than scan positions, leading to signal blockage between the scanner and the top of vegetation. Consequently, the corrected
DTM with application of a global correction factor is lower than the reality. To minimize the error based on these vegetation characteristics, this research applies an adaptive DTM correction factor for those areas covered by smooth cordgrass. Fan (2014) explored the relationship between vegetation height and errors, and he found average penetration depth, which was equivalent to the difference between the grass height and vegetation error, was about 35% of the grass height. Errors were derived by subtracting the surveyed GNSS elevation from the DTM elevation at the corresponding x/y coordinate. The grass height can be calculated by subtracting DTM from DSM, so errors have a correlation with the subtraction of DTM from DSM and the equation is

\[
\text{Errors} = (1 - 35\%) \times (\text{DSM} - \text{DTM}) = 0.65 \times (\text{DSM} - \text{DTM}) = 0.65 \times \text{DSM} - 0.65 \times \text{DTM} \quad (1)
\]

Based on the above correlation, the calculation of errors is feasible and these errors are adaptive correction factors for DTM correction. In this research, the initial DTM and DSM are different from the reality due to the signal blockage in dense tall vegetation. The exploration of new correlation equation is necessary and adaptive correction factors for this research are derived with the new equation.

According to the accuracy analysis of the initial DTM, dense tall vegetation has significant impacts on mapping accuracy. The classification process classified the berm into tall vegetation, low vegetation and bare ground. Based on the classification result, the DTM for tall and low vegetation was corrected separately. Previous research has applied correction factors to modify the classified DTM and achieved a significant improvement (Hladik and Alber 2012; Hladik, Schalles et al. 2013). However, experiment in this research showed that assigning a single global correction factor resulted significant reduction in mean error but not in the RMSE, which indicates over correction in some areas. This is partly due to the height variation from tall vegetation with
different status such as healthy vegetation and stressed vegetation due to wind, salinity, inundation, growth stages, and human disturbance,

To solve the above problem, this research applied an adaptive correction factor for tall vegetation based on local condition. The adjusted correction factor was decided by exploring the correlation between errors and the initial DTM and DSM. The construction of correlation involved 800 GNSS points in the tall vegetation to derive the adjusted correction factor. Equation 2 shows the correlation between errors and the initial DTM and DSM.

\[
\text{Errors} = 1.055 \times \text{DTM} - 0.019 \times \text{DSM} - 0.284
\]  

(2)

The R square of the regression equation is as high as 0.733 and figure 8 shows the points scattering. With the subtraction of the adjusted correction factor from the initial DTM for tall vegetation, DTM correction was achieved. Figure 9 shows the corrected DTM for tall vegetation.

![Figure 8. Relationship between errors and initial DTM](image)
**Figure 9. Corrected DTM for tall vegetation**

*DTM Correction for Low Vegetation*

Compared with smooth cordgrass, seashore paspalum in the study site is lower with an average height of 0.37 m based on the vegetation plot surveys, which is lower than the height of the scanner. As a result, the laser signal launched from the scanner can hit the top of most vegetation to generate a more accurate DSM than DTM. However, most research applied correction factors based on DTM instead of DSM to correct DTM when using airborne LiDAR data. Hladik and Alber (2012) corrected DTM in vegetated coastal environments using mean error as the correction factor and improved the accuracy of LiDAR-derived DTM. They calculated the mean error for each land cover class by subtracting the GPS-surveyed elevation from the DTM and averaging them into one single correction factor.
For DTM correction in the areas with low vegetation and relatively homogenous crown height, this research derived the correction factor based on DSM, meaning that the final DTM was produced by subtracting the correction factor from the DSM. In addition to the mean error, other statistical parameters, such as root mean square error (RMSE) and 95th percentile error, were tested as well. The correction factor with the highest accuracy was applied to correct the DTM. After the DTM correction for the areas with low and tall vegetation respectively, the corrected DTMs were merged with the DTM in bare ground together.

In this study, the correction factor was calculated by subtracting the surveyed GNSS data from the DSM elevation at the x/y coordinate of the GCP and deriving the statistical parameter. The final elevation was obtained by subtracting the correction factor from the DSM elevation.

\[
\text{Final Elevation} = \text{DSM} - \text{Correction Factor} \tag{3}
\]

Representing the average difference between the DTM and GNSS elevations, the mean error has been applied as correction factor to modify the DTM successfully (Hladik and Alber 2012). The mean error works effectively when the vegetation condition in the study area is consistent, meaning that the errors caused by vegetation block do not vary widely. In this research, the low vegetation presented a diverse height, leading to a wide range of errors. Consequently, the DTM correction with mean error as correction factor may result a low-accuracy product. In addition to the mean error, other statistical parameters derived from errors were also tested. After correcting DTMs by applying the mean error and the 95th percentile error as correction factors, the 95th percentile error (0.58 m) as correction factor produced the DTM with the highest accuracy. Mean bias error (MBE) and root mean square error (RMSE) were applied to assess the accuracy of the corrected DTMs. The DTM correction by the factor 95th percentile error produces a lower MBE and RMSE, meaning that the correction with factor 95th percentile error leads to a DTM
with higher accuracy. After the correction for both tall vegetation and low vegetation, all the corrected DTMs were merged into the final DTM (Figure 10).

Table 2. Accuracy assessment for DTM correction by different factors

<table>
<thead>
<tr>
<th>Correction Factor</th>
<th>MBE (m)</th>
<th>RMSE(m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Error</td>
<td>0.12</td>
<td>0.19</td>
</tr>
<tr>
<td>95th Percentile Error</td>
<td>-0.06</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Figure 10. Corrected DTM for low vegetation
4.3 Comparison with Existing Correction Methods

Adjusting window size is an alternative method to filter the ground in vegetated area. A larger window size could increase the chance of finding a nearby ground and therefore reduce the error in estimation of ground elevation. However, this will sacrifice topographical detail. The accuracy and the spatial characteristics of terrain surface need balance when selecting the window size. How filter window size affects the accuracy of DTM correction was studied for areas with low vegetation and tall vegetation respectively. The window size was initially set as 6×6 cm$^2$, the same resolution as DTM, and then it was increased from 10×10 cm$^2$ to 100×100 cm$^2$. This research assessed the accuracy of DTMs at each window size for low-vegetation and tall-vegetation areas respectively and compared them with the results achieved by our methods.
Figure 12. Errors comparison for tall vegetation

Figure 13. Errors comparison for low vegetation
For tall-vegetation area, the RMSE and MBE decrease gradually with the increasing of the filtering window size except at 10 cm where the maximum errors present. Although setting the window size as 100 cm, the RMSE and MBE are still 0.63 m and 0.76 m respectively, which are too high for topographical analysis in addition to significant reduction in topographical detail. In contrast, the RMSE and MBE are reduced to 0.17 m and -0.10 m by using the proposed method with 6 cm window size. The RMSE and MBE for low-vegetation area show the same trend as those for tall-vegetation area. With the application of our method, the RMSE and MBE are also improved significantly to 0.15 m and -0.06 m.

4.4 Summary

This chapter introduces a rapid and flexible terrain mapping solution for densely vegetated environment by integrating crown structure from terrestrial LiDAR with terrain samples from GPS. An iterative ground filtering process first generates the initial DTM with significant overestimation in vegetated areas. A terrain correction process classifies the landscape based on the segmentation and supervised SVM classification method and then corrects terrain in vegetated areas based on the errors from the training samples in the corresponding class.

To improve the accuracy through incorporating vegetation characteristics, this research tested different approaches and proven the best approach to assign correction factor is through a linear regression with DTM in tall vegetation and 95-percentile terrain error in low vegetation. Comparing to typical usage of mean error, the terrain correction factor in tall vegetation is therefore adaptive to local terrain condition. The validated results in a wetland restoration site demonstrated that the proposed method successfully corrected the mean errors from 0.407 m to -0.068 m in low vegetation and from 0.993 m to -0.098 m in tall vegetation.
One major challenge in this research is the land-cover classification based on terrestrial LiDAR without depending on historical data or other images, which is critical for the ever-changing coastal landscapes. The object-oriented classification with four statistic rasters as input can separate the land cover into tall vegetation, low vegetation and bare ground, which is the basis for next step DTM correction. In the process of the object-oriented classification, a threshold-based classification separates bare ground from low and tall vegetation after the segmentation. Then a supervised SVM classification classifies the remaining objects into low and tall vegetation. The overall accuracy and kappa value for object-oriented classification are 92.7% and 0.89 comparing to 82.0% and 0.73 from the pixel-based classification method. The results demonstrates that the object-oriented method can yield a better classification result.

Based on the classification result, DTM correction was conducted for low vegetation and tall vegetation separately. For tall vegetation, statistical correlation between error and original DTM was applied to correct DTM. Comparing to typical usage of mean error, the terrain correction factor in tall vegetation is therefore adaptive to local terrain condition. For low vegetation, the study corrects the terrain by subtracting the correction factor 95th percentile error from the DSM elevation. Both corrected DTMs have better results than those corrected by the existing method of adjusting filter window size. The terrain correction method successfully reduced the mean error from 0.407 m to -0.068 m (RMSE errors from 0.425 m to 0.146 m) in low vegetation and from 0.993 m to 0.094 m (RMSE from 1.070 m to 0.144 m) in tall vegetation. With the high resolution of 6 cm and high accuracy, the corrected DTM is a reliable data source for further coastal morphological analysis.
Chapter 5. Object-Oriented Multi-temporal Sediment Change Analysis

5.1 Introduction

Sediment change is a critical issue in riverine, estuary and coastal environments, related to a wide range of concerns such as land loss, bank erosion, wetland degradation, barrier island protection, and wildlife conservation (Coleman, Roberts et al. 1998; Morton, Bernier et al. 2006). Especially in areas with low gradient topography like coastal wetlands, small elevation changes in few centimeters can sometimes significantly alter salinity and inundation impact and hence transform the distribution of vegetation species (Kulawardhana, Popescu et al. 2014; Kulawardhana, Feagin et al. 2015). As an ancillary data resource, topographic models can be further integrated with other dataset to assist classifications of land cover/use types, vegetation species, mineral types, wildlife habitats, and estimation of carbon stocks (Zhang and Xie 2013; Kulawardhana, Popescu et al. 2014). All these important applications rely heavily on accurate and timely topography mapping.

Traditional methods for monitoring sediment change include measurement of elevation profiles, video imagery, and laser profiling. Cross-section elevation profiling at discrete sample locations is a frequently used method in both wave tank experiments and in the field (Coops, Geilen et al. 1996; Masselink and Pattiaratchi 2001; Yuan, Wu et al. 2011). Coops, Geilen et al. (1996) used recording poles to determine elevation profiles and volume change in an outdoor wave tank experiment, a simple yet effective method to monitor sediment variations. However, considering the spatial heterogeneity of beaches, analysis based on a limited number of profiles may be insufficient for accurate calculation of morphological changes over the entire area (Palmsten and Holman 2012). This method may overlook areas with severe sediment change because of the necessity to predetermine profile locations for periodical survey yet the difficulty
in predicting locations of severe change. Higher accuracy generally requires a larger array of sensors or more measurements (Erikson and Hanson 2005), which can be challenging and costly in both laboratory and field environments using these discrete measurement methods. Therefore, methods with non-intrusive and continuous surface mapping are preferred for many applications.

Known as a high-precision and dense mapping tool, terrestrial LiDAR technology has become more reliable and affordable as well as gained popularity in various field applications (Meng, Wang et al. 2009; Meng, Wang et al. 2009; Zhao, García et al. 2015). In recent years, terrestrial LiDAR has demonstrated great advantages for quick, accurate, and dense 3D topographic mapping. With the accurate topographic mapping from different time, sediment change analysis is possible by comparing the topography before and after a natural event. Therefore, accurate topography mapping is the key to analyze sediment change.

In this study, the proposed methodology in chapter 4 produces a corrected DTM from terrestrial LiDAR data by integrating crown structure from terrestrial LiDAR with terrain samples from GPS. The method improves the accuracy of the DTM significantly for the vegetated area after the terrain correction. With the high resolution as 6 cm and high accuracy, the corrected DTM is a reliable data source for further sediment change analysis. The terrestrial LiDAR data collected for the study site ranges from 2014 to 2016. With all three corrected DTMs, yearly sediment change analysis is feasible. An object-oriented sediment change analysis was applied to identify the significantly erosional and depositional areas for the study site to assess the effectiveness of wetland restoration. In order to validate the method for sediment change analysis, this study conducted a laboratory experiment to explore the application of object-oriented sediment change analysis and applied the method in field data. The laboratory experiment has been published as a
5.2 Laboratory Validation of Object-Oriented Sediment Change Analysis

5.2.1 Laboratory Experiment Setup, Data Collection and Processing

The experiment was conducted in an indoor wave tank at Louisiana State University as illustrated in Figure 14. This wave tank is 8.74 m long, 5.7 m wide and 0.30 m deep and equipped with a wave generator mounting a LDT (Linear Displacement Transducer) position-sensing system made by MTS Systems Corporation. The WAVCIS Lab at Louisiana State University operates the whole system. The distance from the front surface of the wave maker to the end of the wave tank is 6.83 m. The sand, with a sorting coefficient of 0.48, has a slight coarse skew with a skewness value of 0.11. The sand has a mean grain size of 0.34 mm and density of 2.65 g/cm³. Figure 15 illustrates the initial beach created at the end of the wave tank with a slope of 15° and five beach profiles with an approximate cross-profile distance of 0.93 m for elevation change analysis. The distance from the beachfront to the wave maker front was approximately 3 m.

To conduct multi-temporal beach evolution experiment, the wave generator was programmed to produce continuous waves with 0.499 Hz (2 s period) sine waves for three ten-minute applications and terrestrial LiDAR was used to map the beach morphology before and after each wave application. To capture the entire beach, this experiment conducted multi-site scans at two locations near the end of the wave tank for each survey and added a third location at the side of the beach during the last survey to capture a deeply eroded area that might have been blocked from the other two locations. Four highly reflective cylindrical targets provided by the LiDAR system were evenly distributed around the tank (Figure 14) before and after each 10-min wave application to ensure consistent registration from multi-site and multi-temporal scanning. As a
result, four topographic models acquired under no water condition were used in the following beach analysis.

Figure 14. Bird's-eye view of the initial experimental setup from the 3D data obtained by terrestrial LiDAR

Figure 15. The initial beach with a slope of approximately 15°
The terrestrial LiDAR system scanned the beach with a 0.002° resolution and a scanning range of 500 m (the minimum scanning distance with a setting of 300 kHz laser pulse repetition rate and 122,000 measurements/second). Four highly reflective cylindrical targets were distributed around the wave tank and fine scanned during each survey. The LiDAR operation system RiSCAN PRO software used a multi-site registration function and the four targets to accurately register all data from 17 panorama scans through one time of registration process. The data for the four beach statuses without water were used for the following analysis. The derived data have an average point density of 4 points/cm² for two scan positions and 11 points/cm² for three scan positions. The data for each beach mapping were then interpolated into topographic beach models using Kriging interpolation method. Tests of other interpolation methods indicated no significant difference with this dense data. The registration process produced a standard deviation of 0.009 m. To assess the potential errors introduced by the multi-site and multi-temporal scanning and registration process, this experiment used thirty randomly distributed points in the undisturbed beach at the end of the wave tank based on the first and last beach models with 1 cm resolution. The results showed an accuracy of -0.002 m ± 0.003, indicating no significant errors introduced.

5.2.2 Object-Oriented Method of Sediment Change Analysis

Given two topographic models, the elevation change is represented by subtracting an earlier model from the next in the time sequence. For the elevation change, a positive value represents sediment deposition, a negative value represents sediment erosion, and zero value represents no change. The elevation change value is divided into three categories and the statistic information is calculated for each category respectively. In previous studies, the method for sediment change analysis is commonly pixel-based, but this method contains the noise from data processing. Moreover, individual erosional or depositional patches cannot be pointed out clearly.
because of the surrounding noisy points. Therefore, the studies using pixel-based method only reported the overall results for erosion and deposition, ignoring those areas with distinct erosion and deposition. Considering this problem, the object-oriented method is designed to define the topographic surface as a series of discrete and identifiable objects instead of arrays of pixels.

In recent years, a simple effective object-oriented tool, Coastal Morphology Analyst (CMA), has been developed for coastal morphological change analysis by Liu, Wang et al. (2010). This tool provides a way to examine sediment change patterns and has a great potential in applications such as beach nourishment. The algorithm in the tool explicitly identifies and delineates individual erosion and deposition zones as discrete objects, which are represented by a number of polygon features. The erosion and deposition objects, instead of pixels, are input as basic units for sediment change analysis. Two-dimensional planimetric and three-dimensional volumetric attributes are derived for all the objects. Represented by objects, the erosion and deposition zones are easy to localize and their clear spatial pattern is essential for coastal morphological analysis. The object-oriented results are useful for coastal management because of the explicit erosion and deposition zones. The polygon features derived from the object-oriented method are ancillary data resources for further analysis integrated with other GIS data.

This study applied CMA into multi-temporal sediment change analysis. Based on a predefined threshold of elevation change value, each pixel is then classified as erosional, depositional, or area of no significant change. Users can define this threshold based on their need or preferences in certain applications. The remaining pixels with elevation change within the threshold are classified as areas with no significant change. Based on maps of these elevation changes and classified labels, the CMA method then forms object boundaries by grouping neighboring pixels with the same erosional or depositional labels. In order to eliminate salt-and-
pepper noises from small and random pixels, CMA applies the minimum pixel number of an object to determine the minimal object size.

5.2.3 Results of Laboratory Experiment

Scanned by terrestrial LiDAR, a set of topographic products are produced, including topographic model, slope map, aspect, and hill-shaded relief map. Sediment in the middle and upper areas of the swash zone was washed downslope and deposited at the beachfront. The most significant sediment erosion occurred at the middle area of the beach, forming a pond. Figure 16(a) shows the hill-shaded relief map of the laboratory beach morphology with an enhanced 3D perception, which is especially useful for the analysis of low-relief areas such as ripple patterns. These results demonstrate the advantage of high-resolution mapping to detect morphological features with smaller sizes. The smallest morphological feature detected in this 1 cm resolution model is the 3 cm wide ripples at the beachfront. The ripples on the floor were mainly distributed at the center half of the tank due to the proximity to the most severely eroded upper areas and the interference of sidewalls with water waves. Figure 16(b) shows a contour map with 5 cm intervals overlaid on top of the 1 cm resolution topographic model. Comparing to the hill-shaded relief map, the contour map generalizes the topography into a few zones of equal elevation ranges and provides effective assistance in recognizing elevation trends and patterns. The slope map in Figure 16(c) highlights areas with steep slopes in red; this can be used as a tool to enhance ripple patterns as well as to locate areas of significant sediment erosion. The pixel-based map of elevation changes in Figure 16(d) shows that the elevation changes range from -0.176 m to 0.167 m. The most significantly eroded area locates at the center of the beach with gradual decline to both sides. The most significantly deposited areas include the lower elevation area right next to the significantly eroded area and the areas next to the walls on both sides.
Based on the elevation change map, CMA identified a total of nineteen objects (ten erosional and nine depositional) outlined by fitted ellipses illustrated in Figure 17 with a focus on significantly changed areas over 2 cm in elevation and over a minimum of 50 pixels. Attributes of each object including location, area, volume, and object type are listed in Table 3, which is organized by object type and volume. The location of each object was represented by the center coordinate of the corresponding fitted ellipse. Tables 4 and 5 summarize statistics of sum, minimum, maximum and standard deviation of area and volume for the identified objects. The total erosional and depositional areas were 4.5525 m$^2$ and 4.8904 m$^2$, respectively. The erosional objects have a minimal area of 0.0063 m$^2$ and a maximal area of 4.3522 m$^2$; while depositional objects have a minimal area of 0.2 m$^2$ and maximal area of 0.0173 m$^2$. The standard deviation of
erosional objects (1.3695 m$^3$) is approximately twice as that of the depositional area (0.7861 m$^3$), indicating that the size of erosional objects varies more than the size of depositional objects. Meanwhile, the total erosional and depositional volumes are 0.398341 m$^3$ and 0.232801 m$^3$, respectively, ranging from minimal volumes of 0.000137 m$^3$ and 0.000429 m$^3$ to maximal volumes of 0.393447 m$^3$ and 0.09923 m$^3$. Erosional objects also vary more than depositional objects in terms of the volume due to a larger standard deviation. The average thickness of objects was calculated as total volume divided by total object area. For this experiment, the average thickness of erosional and depositional objects was 0.087 m and 0.048 m, respectively. Thus, the average thickness of erosional objects was almost twice as that of depositional objects.

The results in Figure 18 and Figure 19 demonstrate the observation of beach evolution based on CMA. Majority of the erosional and depositional areas were formed after the first period of wave application (P1). The erosional volume was 0.2925 m$^3$ while the depositional volume was 0.1750 m$^3$, with a difference of 0.1075 m$^3$. This difference was caused by two factors: (1) layers of dispositional and erosional areas that were thinner than 2 cm were not included, and (2) when detecting objects, small and fragmented areas with fewer than 50 pixels were not considered as significant areas for statistics. During the following periods of wave application, P2 and P3, decreasing number of areas and volumes of sand were eroded and deposited. After the second period (P2), the erosional volume was 0.1017 m$^3$ and the depositional volume was 0.0732 m$^3$ with a difference of 0.0285 m$^3$. After the third period (P3), the erosional volume was 0.0387 m$^3$ and the depositional volume was 0.0235 m$^3$ with a difference of 0.0152 m$^3$. In these last two periods, areas and volumes of both erosion and deposition did not change as much as in the first period, but more ripple patterns were formed at the beachfront. Overall, the amount of significantly changed areas decline as the time increases, showing a sediment stabilization trend.
Table 3. Attributes of objects identified from CMA sorted by object type and volume

<table>
<thead>
<tr>
<th>Object ID</th>
<th>Object Type</th>
<th>Location-X (m)</th>
<th>Location-Y (m)</th>
<th>Area (m²)</th>
<th>Volume (m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>Erosion</td>
<td>3.5</td>
<td>4.61</td>
<td>4.3522</td>
<td>0.393447</td>
</tr>
<tr>
<td>14</td>
<td>Erosion</td>
<td>6.36</td>
<td>3.62</td>
<td>0.0964</td>
<td>0.002408</td>
</tr>
<tr>
<td>1</td>
<td>Erosion</td>
<td>4.8</td>
<td>0.63</td>
<td>0.0214</td>
<td>0.000513</td>
</tr>
<tr>
<td>8</td>
<td>Erosion</td>
<td>5.19</td>
<td>2.61</td>
<td>0.0207</td>
<td>0.000495</td>
</tr>
<tr>
<td>11</td>
<td>Erosion</td>
<td>4.33</td>
<td>2.76</td>
<td>0.0142</td>
<td>0.000337</td>
</tr>
<tr>
<td>19</td>
<td>Erosion</td>
<td>1.92</td>
<td>4.2</td>
<td>0.0132</td>
<td>0.000334</td>
</tr>
<tr>
<td>17</td>
<td>Erosion</td>
<td>6.01</td>
<td>3.89</td>
<td>0.0111</td>
<td>0.000262</td>
</tr>
<tr>
<td>12</td>
<td>Erosion</td>
<td>4.3</td>
<td>2.9</td>
<td>0.0095</td>
<td>0.000224</td>
</tr>
<tr>
<td>8</td>
<td>Erosion</td>
<td>2.04</td>
<td>4.12</td>
<td>0.0076</td>
<td>0.000185</td>
</tr>
<tr>
<td>2</td>
<td>Erosion</td>
<td>5.32</td>
<td>1.04</td>
<td>0.0063</td>
<td>0.000137</td>
</tr>
<tr>
<td>7</td>
<td>Deposition</td>
<td>3.01</td>
<td>3.06</td>
<td>2.2086</td>
<td>0.09923</td>
</tr>
<tr>
<td>5</td>
<td>Deposition</td>
<td>5.5</td>
<td>2.71</td>
<td>1.1516</td>
<td>0.066502</td>
</tr>
<tr>
<td>16</td>
<td>Deposition</td>
<td>1.6</td>
<td>4.33</td>
<td>1.1699</td>
<td>0.057753</td>
</tr>
<tr>
<td>13</td>
<td>Deposition</td>
<td>4.23</td>
<td>3.26</td>
<td>0.099</td>
<td>0.002804</td>
</tr>
<tr>
<td>6</td>
<td>Deposition</td>
<td>2.23</td>
<td>2.28</td>
<td>0.1084</td>
<td>0.002502</td>
</tr>
<tr>
<td>9</td>
<td>Deposition</td>
<td>4.78</td>
<td>2.61</td>
<td>0.0674</td>
<td>0.001759</td>
</tr>
<tr>
<td>3</td>
<td>Deposition</td>
<td>4.14</td>
<td>1.25</td>
<td>0.0362</td>
<td>0.000977</td>
</tr>
<tr>
<td>10</td>
<td>Deposition</td>
<td>1.45</td>
<td>2.7</td>
<td>0.032</td>
<td>0.000846</td>
</tr>
<tr>
<td>4</td>
<td>Deposition</td>
<td>2.46</td>
<td>1.57</td>
<td>0.0173</td>
<td>0.000429</td>
</tr>
</tbody>
</table>
Table 4. Area statistics of erosional and depositional objects

<table>
<thead>
<tr>
<th>Object Type</th>
<th>Object Quantity</th>
<th>Sum of Area (m²)</th>
<th>Minimal Area (m²)</th>
<th>Maximal Area (m²)</th>
<th>Std. Deviation of Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deposition</td>
<td>9</td>
<td>4.8904</td>
<td>0.0173</td>
<td>2.2086</td>
<td>0.7861</td>
</tr>
<tr>
<td>Erosion</td>
<td>10</td>
<td>4.5525</td>
<td>0.0063</td>
<td>4.3522</td>
<td>1.3695</td>
</tr>
</tbody>
</table>

Table 5. Volume statistics of erosional and depositional objects

<table>
<thead>
<tr>
<th>Object Type</th>
<th>Object Quantity</th>
<th>Sum of Volume (m³)</th>
<th>Minimal Volume (m³)</th>
<th>Maximal Volume (m³)</th>
<th>Std. Deviation of Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deposition</td>
<td>9</td>
<td>0.232801</td>
<td>0.000429</td>
<td>0.09923</td>
<td>0.0381</td>
</tr>
<tr>
<td>Erosion</td>
<td>10</td>
<td>0.398341</td>
<td>0.000137</td>
<td>0.393447</td>
<td>0.1242</td>
</tr>
</tbody>
</table>

Figure 18. Beach evolution based on CMA analysis. The upper figures are beach models showing initial model (a) and models after 1 (b), 2 (c), and 3 (d) periods of wave application. Figures (e)-(f) show the changing areas of sediment erosion and deposition between consecutive beach models that occurred after 1 (e), 2 (f), and 3 (g) periods of wave application. Each period of wave application lasted 10 minutes.
One practical and common need in sediment change analysis is to locate severely eroded areas and estimate sediment volume for nourishment of beaches, berms and levees, which have wide applications in wetland restoration, barrier island protection and levee monitoring. Comparing to the commonly used sediment change analysis based on elevation change map, the recently developed CMA tool provides an effective yet simple approach to identify areas with significant erosion and deposition along with statistics on object-based attributes such as shape, area, volume, and thickness. As an application example for sediment change, CMA provides an effective tool for identifying the top four erosional objects (with volumes close to or more than 0.0005 m$^3$) and the top three depositional objects (with volume larger than 0.057 m$^3$, Table 3). When applied to outdoor environment, this information can support planning of beach nourishment to identify locations that needed nourishment and their area and volume for cost assessment.

When applied to multi-temporal beach models (Figure 18), CMA can provide a new perspective for sediment evolution analysis that differs from traditional pixel- and profile-based approaches. Users can specify a threshold of elevation change level for areas with obvious or severe sediment erosion and deposition, which correspond to areas of concern. In addition, the
evolution patterns presented by the CMA method are simple and straightforward, which reduce the uncertainties introduced by different interpretations from users.

5.3 Object-Oriented Sediment Change Analysis for Field Data

As proved by the laboratory experiment in the above section, the object-oriented method is efficient for the sediment change analysis based on the terrestrial LiDAR data. For the study site, the terrestrial LiDAR data was collected on 30 July 2014, 1 October 2015, and 29 October 2016 respectively. By applying the proposed method in chapter 4, the high-resolution DTMs have been produced for all three years. After the generation of all three accurate DTMs, yearly sediment change can be derived using the object-oriented method proposed in the section 5.2.

5.3.1 Validation of Yearly Change map

The first step of the object-oriented sediment change analysis is to generate a pixel-based change map. The quality of the pixel-based change map influences the results of the object-oriented sediment change analysis, so validation of the pixel-based change map is necessary. In the same field campaign of terrestrial LiDAR scan, six transects were surveyed with RTK GPS in both 2015 and 2016. Five of the six transects were perpendicular with the berm direction and the other one was along the berm direction (Figure 20). To validate the elevation change from the corrected DTMs between 2015 and 2016, its value \( (\text{DTM}_{2016} - \text{DTM}_{2015}) \) was compared with that derived from the GPS samplings.
Figure 20. Transects distribution on the berm

Figure 21. Transects comparison between elevation change (2015-2016) derived from DTM and GPS

Figure 21 shows the elevation change (2015-2016) derived from corrected DTMs (lines with diamond markers) and GPS samplings (lines with square markers) separately. For all six transects, the elevation change derived from DTMs keeps the same trend with that from GPS.
samplings. At the end of transects T1, T2 and T5, the elevation change from DTMs and GPS shows inconsistent for a short interval. All these points are located at the edge of the berm, where elevation is lower than other areas and vegetation cover is relatively dense, causing the lower accuracy of DTM correction than the remaining areas. However, the whole trend of the elevation change shows consistent in most areas from DTMs and GPS samplings. In other words, calculating the elevation change from the corrected DTMs reveals the consistent performance with reality, and it is reliable for the next-step sediment change analysis.

5.3.2 Results of Object-Oriented Sediment Change Analysis

The study applied the CMA analysis for yearly sediment change of the study site from 2014 to 2016. As proved in the previous section, the elevation change map (2015 – 2016) generated from the corrected DTMs is reliable. Two yearly elevation change maps (Figure 22) were generated for CMA analysis. From 2014 to 2015, most of the erosion occurs on the northeast side of the berm while the deposition occurs on the southwest side of the berm. The elevation difference ranges from -0.82 m to 0.25 m. From 2015 to 2016, the erosion also occurs mostly on the northeast side of the berm and the elevation difference ranges from -0.62 m to 0.57 m.

Based on the elevation change map from 2014 to 2015, CMA identified 259 objects (228 erosional and 31 depositional) outlined by fitted ellipse with a focus on significantly changed areas over 40 cm in elevation and over a minimum of 100 pixels. The CMA analysis used the same parameters for 2015 to 2016, and identified 482 objects (170 erosional and 312 depositional). Figure 23 illustrates the identified objects by CMA analysis.
Figure 22. (a) Elevation change map from 2014 to 2015, (b) elevation change map from 2015 to 2016
Figure 23. (a) Significantly eroded and deposited objects identified by CMA for based on terrain models for 2014 to 2015, (b) objects identified by CMA for 2015 to 2016
Table 6. Area statistics of erosional and depositional objects

<table>
<thead>
<tr>
<th>Period</th>
<th>Object Type</th>
<th>Object Quantity</th>
<th>Sum of Area (m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014-2015</td>
<td>Deposition</td>
<td>31</td>
<td>99.76</td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>228</td>
<td>2737.77</td>
</tr>
<tr>
<td>2015-2016</td>
<td>Deposition</td>
<td>170</td>
<td>684.67</td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>312</td>
<td>291.55</td>
</tr>
</tbody>
</table>

Table 7. Volume statistics of erosional and depositional objects

<table>
<thead>
<tr>
<th>Period</th>
<th>Object Type</th>
<th>Object Quantity</th>
<th>Sum of Volume (m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2014-2015</td>
<td>Deposition</td>
<td>31</td>
<td>51.79</td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>228</td>
<td>1621.78</td>
</tr>
<tr>
<td>2015-2016</td>
<td>Deposition</td>
<td>170</td>
<td>358.52</td>
</tr>
<tr>
<td></td>
<td>Erosion</td>
<td>312</td>
<td>150.20</td>
</tr>
</tbody>
</table>

Tables 6 and 7 summarize statistics of area and volume for the identified objects. For 2014 to 2015, the total significant erosional and depositional areas are 2737.77 m² and 99.76 m², respectively; while for 2015 to 2016, the total significant erosional and depositional areas are 291.55 m² and 684.67 m², respectively. Meanwhile, the total erosional and depositional volumes are 1621.78 m³ and 51.79 m³ for 2014 to 2015; while the total erosional and depositional volumes are 150.20 m³ and 358.52 m³, respectively. The significantly eroded objects indicate areas that needed berm nourishment to improve wetland engineering.
Figure 24. Sediment change based on CMA analysis. The upper figures are corrected DTM for years 2014 (a), 2015 (b) and 2016 (c). Figures (d)-(e) show the changing areas of sediment erosion and deposition between consecutive DTM.
For 2014 to 2015, 88% of the identified objects are erosional, which are mostly focused on the northeast side of the berm. The berm was constructed in 2014 with vegetation planted, causing the berm covered by sparse and young vegetation for a certain time from 2014 to 2015. Therefore, the erosion is stronger than the following years. For 2015 to 2016, 65% of the identified objects are depositional, caused by the vegetation cover that can hold sediment from erosion. With the objects identified by CMA analysis, the erosional and depositional areas were located and the associated statistic information was calculated. The object layers are a type of data source for vegetation pattern analysis.

5.4 Summary

This chapter applied CMA analysis to study the multi-temporal sediment change for the study site. First, with an indoor experiment setup, the object-based coastal morphological analysis tool CMA was applied to detect significant erosional and depositional areas. Nineteen objects (ten erosional and nine depositional) were identified with location, area and volume attributes to support analysis of the distribution of erosion and deposition. As an object-based morphological analysis, CMA can analyze morphological change in aggregated areas and determine geometry and statistical attributes for each object, which is useful for identifying significantly erosional and depositional areas. The integration of terrestrial LiDAR and CMA was examined in an indoor environment and was proved as a successful method for identifying and analyzing wave-induced erosion and deposition.

Second, based on the DTMs corrected from chapter 4, CMA analysis was applied to detect the yearly sediment change. Elevation change map is the basis of CMA analysis, so the accuracy of elevation change is essential for the reliability of CMA analysis. The elevation change map (2015-2016) calculated from the corrected DTMs was compared with that derived from GPS
samplings. In both 2015 and 2016, six transects were surveyed using GPS for the generation of elevation change map as truth data. By comparison, the whole trend of the elevation change shows consistent in most areas from DTMs and GPS samplings. In other words, calculating the elevation change from the corrected DTMs reveals the consistent performance with reality, and it is useful for the next-step sediment change analysis.

Last, based on the elevation change map derived from the corrected DTMs, CMA analysis was performed for the study site. CMA identified 259 objects (228 erosional and 31 depositional) outlined by fitted ellipse with a focus on significantly changed areas in elevation and over a minimum of 100 pixels. The CMA analysis used the same parameters for 2015 to 2016, and identified 482 objects (170 erosional and 312 depositional). The identified erosional and depositional objects are useful data source for coastal wetland restoration. Meanwhile, the object-oriented sediment change is also an essential data input for vegetation pattern analysis in next chapter.
Chapter 6. Correlation Exploring Between Vegetation Competition and Sediment Change

6.1 Introduction

The role of micro-topography in wetland restoration attracts more attention from wetland ecologists as restoration techniques continue to evolve and improve (Reed-Dustin, Paulus et al. 2012). Micro-topography is an essential variable to measure for modeling water movement (Dunne, Zhang et al. 1991), vegetation dynamics (Beatty 1984; Enoki 2003) and surface roughness (Kamphorst, Jetten et al. 2000). Previous studies have shown that micro-topography and its associated topographic variables, such as slope, aspect and curvature, are closely related to soil depth, nutrient status and water status (Lassueur, Joost et al. 2006). Therefore, high-accuracy micro-topography mapping and its associated topographic variables can lead to improved estimates of water storage and infiltration and facilitate high-resolution digital soil mapping (Brubaker, Myers et al. 2013). Because of the ability to influence wetland hydrology and habitat variability, micro-topography is important in determining vegetation patterns (Moser, Ahn et al. 2007). Alexander, Deak et al. (2016) studied the micro-topography driven vegetation patterns in open mosaic landscapes and found the vegetation pattern of alkali landscapes shows a high correlation with the position of water table and salt accumulation, which are strongly correlated with micro-topography. Moser, Ahn et al. (2007) identified the characterization of micro-topography and its influence on vegetation patterns in created wetlands. Their results suggest that disking may improve the wetland mitigation better by enhancing vegetation community development.

The study site in this research is a vegetated berm that is constructed to stabilize the wetlands in front of the main levee of Mississippi River. Since different vegetation yields different results for shoreline protection and salinity has a big impact on vegetation distribution, the
effectiveness and suitability of different planted vegetation species are crucial for wetland restoration. In this case, three types of vegetation of smooth cordgrass (spartina alterniflora), seashore paspalum (panicum vaginatum sw), and vetiver grass (chrysopogon zizanioides) were planted horizontally along the ocean side of berm in the mat-protected areas. Smooth cordgrass, as the most effective plant in estuarine shoreline stabilization, was planted on the southwest of the berm to resist waves and saltwater inundation. Vetiver grass and seashore paspalum were planted around smooth cordgrass but closer to the centerline of the berm. After one year of berm construction, majority of vetiver grass died. Smooth cordgrass has grown in dense clusters on both edges of the berm, and seashore paspalum grew in areas with relatively higher elevations. A narrow zone of bare ground surface remained in the center zone of the berm with the highest elevation along the curved sand berm. However, the micro-topography and vegetation pattern have changed in multiple areas on the berm when compared with last year.

In chapter 4, corrected DTMs were produced for each year from 2014 to 2016. In the process of the DTM generation, yearly classification results were created for vegetation pattern analysis in chapter 6. Moreover, a set of associated topographic variables, including slope, hill shade, aspect and topographic wetness index (TWI), were derived for micro-topographic analysis. In chapter 5, yearly sediment change analysis was performed using an object-oriented method. The identified objects with statistic information of elevation change are another input for micro-topographic analysis.

6.2 Exploring Vegetation Pattern Change

For the study site, the berm was reconstructed in 2014 with three types of vegetation, including Chrysopogon zizanioides (Vetiver Grass), Panicum vaginatum Sw (Seashore Paspalum) and salt-tolerant Spartina alterniflora planted from the center of the berm to the edge. However,
after one year of construction, tall and dense Spartina alterniflora colonized the edge of the berm and low and dense Panicum vaginatum Sw covered the areas with relatively high elevation while Chrysopogon zizanioides barely survived. Some studies have shown that topographic factors as the slope and aspect play a greater role than atmospheric temperature in determining the distribution of low-growing vegetation (Scherrer and Korner 2011). Crimmins, Dobrowski et al. (2011) found plants shifting to lower elevation due to changes in plant water balance. Bueno de Mesquita, Tillmann et al. (2018) investigated the influence of fine-scale topographic, snowpack, and soil properties on vegetation change. They suggested that different vegetation types may be sensitive to different aspects of heterogeneity.

During the survey on October 1, 2015, one year after the berm construction, it was found that tall and dense Spartina alterniflora has grouped along the edge of the berm and dense Panicum vaginatum Sw sprawled around the centerline of the berm. These two types of vegetation shared a boundary between them. However, when coming back for yearly survey on October 29, 2016, most of the bare ground was covered by vegetation in the past year. The boundary between two types of vegetation has moved due to their competition. The focus of this section is to detect how vegetation pattern changed from 2015 to 2016, which is the basis of investigating the influence of micro-topography on vegetation pattern. To apply the post-classification technique to detect the change in this section, object-oriented classification was applied for the study site in both 2015 and 2016. Figure 25 shows the classification results for 2015 and 2016.
The classification method for 2016 is same as the classification method for 2015: (1) process the segmentation of the image with multi-resolution segmentation and spectral difference segmentation; (2) threshold classification for bare ground; (3) nearest neighbor classification based on pre-selected training samples. The accuracy assessment for classification of 2016 was performed based on 50 samples for bare ground, 50 samples for low vegetation and 50 samples for tall vegetation. The overall accuracies were 93.3% with kappa statistics of 0.90. User’s
accuracy of individual classes ranged from 90.0% to 98.0% and producer’s accuracy ranged from 88.5% to 91.8%. For the classification result of 2015, as shown in chapter 4, the overall accuracies were 92.7% with kappa statistics of 0.89. User’s accuracy of individual classes ranged from 88.9% to 95.8% and producer’s accuracy ranged from 88.9% to 96.9%. The accuracy assessment proved that the object-oriented method classified the study site with high accuracy and the classification results are qualified for post-classification change detection. The class change between 2015 and 2016 is calculated by subtracting the classification of 2015 from 2016. Figure 26 shows the change detection result between 2015 and 2016.

Table 8 shows the statistic information of the class change from 2015 to 2016. No change area is 3730.26 m² (low vegetation: 894.26 m², tall vegetation: 2524.86 m², bare ground: 344.14 m²). The largest change types are those from bare ground to tall vegetation (2775.15 m²) and from low vegetation to tall vegetation (2214.81 m²), meaning that tall vegetation sprawled and occupied large area from bare ground and low vegetation in one year. The changes from low vegetation to
bare ground and from tall vegetation to bare ground are 23.95 m$^2$ and 3.34 m$^2$ respectively. From Figure 26, the areas changing from tall vegetation to bare ground occurred on the north edge of the berm, where the erosion was very severe from 2015 to 2016. Therefore, the erosion leaded the change from tall vegetation to bare ground, but the change area was only 3.34 m$^2$. For the areas changing from low vegetation to bare ground, one part was also located on the north edge of the berm and the other part was located around the centerline of the berm. The former part was caused by the erosion, but the latter part may be caused by the misclassification. To illustrate the percentage of change status for each class, Figure 27 summarizes the percentage of all change types.

Table 8. Change statistics from 2015 to 2016

<table>
<thead>
<tr>
<th>Change Type</th>
<th>Change Area (m$^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Vegetation to Tall Vegetation</td>
<td>2214.81</td>
</tr>
<tr>
<td>Low Vegetation to Bare Ground</td>
<td>23.95</td>
</tr>
<tr>
<td>Bare Ground to Low Vegetation</td>
<td>482.63</td>
</tr>
<tr>
<td>Bare Ground to Tall Vegetation</td>
<td>2775.15</td>
</tr>
<tr>
<td>Tall Vegetation to Low Vegetation</td>
<td>43.40</td>
</tr>
<tr>
<td>Tall Vegetation to Bare Ground</td>
<td>3.34</td>
</tr>
<tr>
<td>No Change</td>
<td>3730.26</td>
</tr>
</tbody>
</table>

Figure 27. Change status for each class

For low vegetation, 69% of the areas converted to tall vegetation and 30% of the areas remained low vegetation. For tall vegetation, 98% of the areas remained tall vegetation and only 2% of the areas converted to low vegetation. Therefore, more low vegetation converted to tall
vegetation from 2015 to 2016. For bare ground, 77% and 13% of the areas converted to tall vegetation and low vegetation respectively, while only 10% of the areas remained bare ground.

6.3 Micro-Topographic Derived Variables

6.3.1 Generation of Terrain Slope

Terrain slope is the amount of change in elevation over run in some direction, generally the direction for which the rise over run is the greatest (Smith, Goodchild et al. 2007). In other words, terrain slope is the computed as the maximum rate of change in elevation between the location and its surroundings. To generate terrain slope from DTM raster, the maximum rate of change in value from each pixel to its eight neighbors is calculated. The maximum rate of change in elevation over the distance between the pixel and its neighbors represents the steepness. The lower slope value indicates the flatter terrain while the higher slope value indicates the steeper terrain.

Terrain slope is closely related to the rate of surface runoff and accumulation of water flow, and may influence vegetation distribution (Alexander, Deak et al. 2016). Therefore, terrain slope, a micro-topographic derived variable, is useful when studying vegetation patterns. The slope rasters can be output in two types of units, degree or percent. In this study, all the slope rasters were calculated and stored in the unit of degree. Figure 28 shows the terrain slope map in the unit of degree for the study site.
Figure 28. (a) Slope map for 2014, (b) slope map for 2015, (c) slope map for 2016

6.3.2 Generation of TWI

Topographic Wetness Index (TWI), originally developed by Beven and Kirkby (1979), is a steady-state wetness index. TWI has been tested and proved to have high correlations with soil moisture (Zhu, Shi et al. 2014) and it has been applied in vegetation studies (Moeslund, Arge et al.).
2013; Buchanan, Fleming et al. 2014). The index helps identify rainfall runoff patterns and areas of potential increased soil moisture, which are essential factors of vegetation diversity patterns.

TWI is a function of the upstream contributing area and the slope defined as follows:

\[ \text{TWI} = \ln \left( \frac{\alpha}{\tan \beta} \right), \]

Where \(\alpha\) is the local upslope area draining through a certain point per unit contour length and \(\beta\) is the local slope in radians. In this study, TWI was calculated from the corrected DTMs in ArcGIS. First, the sinks in the DTMs were filled for next procedures. Second, flow direction rasters were created from the filled DTMs, and then flow accumulation rasters were estimated from the created direction rasters. The flow accumulation rasters (FLOWACC) were then scaled to \(\alpha = (\text{FLOWACC}+1) \times \) pixel size, where pixel size is 0.06 m in this study. Last, the created slope rasters in section 6.3.1 were converted from the unit of degrees to radians, which were input to calculate the tangents of the slope (\(\tan \beta\)). The yearly TWI maps for the study site from 2014 to 2016 were calculate using the above equation and normalized as follows.
6.3.1 Generation of Other Micro-Topographic Derived Variables

The above two variables of slope and TWI were derived for quantitative analysis between micro-topography and vegetation competition, and other variables including aspect and hill-
shaded relief were also generated from DTM for visual analysis of micro-topographic change. Figure 30 demonstrates the yearly aspect and hill-shaded maps for the study site.

Figure 30. (a) Aspect and hill-shaded relief map for 2014, (b) aspect and hill-shaded relief map for 2015, (c) aspect and hill-shaded relief map for 2016

For the variable of aspect, the map of 2014 shows a separated distribution of directions between northeast and southeast sides of the berm. A line separates two sides of the berm distinctly. The major directions in the northeast side of the berm range from north, east and northeast, while the major directions in the remaining side range from south, west and southwest. For the aspect
map of 2015, only a small area along the centerline of the berm shows a separated distribution of directions, and the remaining areas are occupied by irregular distribution. The irregular distribution of directions prevail the whole berm for the aspect map of 2016. The tendency of irregular distribution of directions is caused by the sediment change. The derived aspect is as high resolution as 6 cm. After the yearly erosion and deposition, the aspect of the berm surface turned more irregular from 2014 to 2016. The hill-shaded relief map displays an enhanced 3D perception, which is especially useful for the analysis of low-relief areas.

6.4 Quantitative Analysis Based on Micro-Topographic Derived Variables

6.4.1 Sediment Change and Micro-Topographic Derived Variables

Micro-topography has been illustrated as a key factor that influences soil erosion evolution (Zheng, Qin et al. 2015). Characterization of micro-topographic spatial variability is essential to model erosive process (Luo, Zheng et al. 2018). With terrestrial LiDAR scanning, a continuous and high-accuracy micro-topographic map and associated products, which are useful for modeling sediment change, can be produced. In the section 6.3, slope and TWI were generated for the study site from 2014 to 2016. These two micro-topographic derived variables represent the characteristic of micro-topography and how they are related to sediment change for the study site needs attention. This section illustrates how sediment change responds to the level of slope or TWI.

In chapter 5, yearly sediment change objects were generated from 2014 to 2016. From 2014 to 2015, the DTM for 2014 represents the pre-event micro-topography and the DTM for 2015 represents the post-event micro-topography. Therefore, the slope and TWI for 2014 indicates the pre-event micro-topographic derived variables. A zonal statistic analysis was applied for the slope and TWI layers for 2014 with sediment change objects as featured zones. The mean value of the slope and TWI were assigned to each sediment change object separately. The sediment change
objects were classified into erosional and depositional objects, and the statistic information of slope and TWI for two types of objects was calculated and compared as Figure 31.

The range of the slope for erosional objects are from 4.0 to 76.9 degree, fully covers the range of the slope for depositional objects that are from 4.4 to 24.4 degree. The results indicate that severely eroded areas occurred more in areas with higher slope, while major depositions usually occurred in areas with lower slope. The practical applications is that berm nourishment should focus more on areas with steep slope, which are typically the surrounding edges of the berm. Compared with the slope, TWI has a stronger capability of separating erosion and deposition. The TWI for erosional objects range from 0.05 to 0.29 and the TWI for depositional objects range from 0.19 to 0.43. The first quartile of the TWI for depositional objects is 0.23 and the third quartile of the TWI for erosional objects is 0.21, so the threshold set bigger than 0.21 and smaller than 0.23 will separate at least 75% of the erosional and depositional objects. Comparatively, major erosion occurred in areas with relatively lower TWI values, and major depositional areas typically have higher TWI values.

The same procedures were performed for the period of 2015 to 2016. The DTM for 2015 represents the pre-event micro-topography and the DTM for 2016 represents the post-event micro-topography. Figure 32 illustrates the statistic information of slope and TWI for two types of objects.
The range of the slope for erosional objects are from 3.5 to 53.8 degree, almost covers the range of the slope for depositional objects that are from 0.7 to 47.3 degree. The TWI for erosional objects range from 0.08 to 0.29 and the TWI for depositional objects range from 0.18 to 0.48. The first quartile of the TWI for depositional objects is 0.27 and the third quartile of the TWI for erosional objects is 0.22, so the threshold set bigger than 0.22 and smaller than 0.27 will also separate at least 75% of the erosional and depositional objects. Similarly, major erosion occurred in areas with relatively lower TWI values, and major depositional areas typically have higher TWI values.

![Figure 32. (a) Statistic information of slope for 2015, (b) statistic information of TWI for 2015](image)

Combing the results for both period from 2014 to 2015 and from 2015 to 2016, the single variable slope cannot separate erosion and deposition, but the single variable TWI is capable of separating at least 75% of the erosional and depositional objects. Major erosion occurred in areas with relatively lower TWI values, and major depositional areas typically have higher TWI values.

6.4.2 Sediment Change and Vegetation Pattern Change

When scanning the berm in 2014 just after the construction, the vegetation was newly planted and the characteristic, especially for the low vegetation, was not detectable. Therefore, the classification was only performed for 2015 and 2016. Based on the object-oriented classification results for 2015 and 2016, the post-classification technique was applied to detect the class change. The class change map was clipped by the sediment change objects, and the class change value of
majority inside the object was assigned to each change object. Figure 33 illustrates the clipped class change map.

Illustrated as Figure 23 (b) in chapter 5, for the sediment change objects, most of the erosional ones locate in the southeast side of the berm while the depositional ones are in the northwest side. Therefore, from Figure 33, the class change types of erosional objects are mainly low vegetation to bare ground and bare ground to tall vegetation. Meanwhile, the class change type of depositional objects is mainly no change. For each class change type, the amount of depositional and erosional objects was calculated separately and assigned to each class change type. Table 9 shows the amount of erosional and depositional objects for each class change type.
Table 9. Amount of objects for change types

<table>
<thead>
<tr>
<th>Change Type</th>
<th>Depositional Objects</th>
<th>Erosional Objects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Vegetation to Bare Ground</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>Low Vegetation to Tall Vegetation</td>
<td>33</td>
<td>51</td>
</tr>
<tr>
<td>Tall Vegetation to Bare Ground</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>No Change (Bare Ground)</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>No Change (Tall Vegetation)</td>
<td>103</td>
<td>21</td>
</tr>
<tr>
<td>No Change (Low Vegetation)</td>
<td>65</td>
<td>20</td>
</tr>
<tr>
<td>Bare Ground to Tall Vegetation</td>
<td>69</td>
<td>84</td>
</tr>
<tr>
<td>Tall Vegetation to Low Vegetation</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>Bare Ground to Low Vegetation</td>
<td>5</td>
<td>10</td>
</tr>
</tbody>
</table>

The statistic information from Table 9 keeps consistent with the image interpretation from Figure 33 (b). Change types of bare ground to tall vegetation and low vegetation to tall vegetation hold the most erosional objects as 84 and 51, respectively. Meanwhile, change types of no change and bare ground to tall vegetation hold the most depositional objects as 176 and 69, respectively. In addition, there are no depositional or erosional objects with the change type of tall vegetation to bare ground. Only two depositional and no erosional objects belong to the change type of tall vegetation to low vegetation. For change types of no change, the most depositional objects (103) are from tall vegetation, so more sediment settled in tall-vegetation area from 2015 to 2016.

6.4.3 Micro-Topographic Derived Variables and Vegetation Pattern Change

Micro-topography plays a role in determining vegetation pattern (Moser, Ahn et al. 2007; Alexander, Deak et al. 2016). This chapter has derived the vegetation change pattern based on the classification results for 2015 and 2016, generated two micro-topographic derived variables, including slope and TWI, and studied the correlation between micro-topographic derived variables and vegetation change pattern. The correlation study is also based on the objects that represent the severe erosion and deposition. As illustrated in the above section, there are no depositional or erosional objects with the change type of tall vegetation to bare ground, and only two depositional
and no erosional objects belong to the change type of tall vegetation to low vegetation. Therefore, the change types of tall vegetation to bare ground and tall vegetation to low vegetation are excluded from this study.

First, for each class change type, the statistic information of the slope was calculated for depositional and erosional objects separately. Figure 34 illustrates the distribution of slope for depositional and erosional objects in each class change type. Only for the class change type bare ground to low vegetation, the variable slope can separate depositional and erosional objects. In other words, for those areas turned from bare ground to low vegetation between 2015 and 2016, the severe erosion was more likely to occur at the place with low slope, which are usually near the center zone of the berm and deposition was the opposite. One possible reason is that areas with initial high slope are usually close to the edge of the berm, where tall and dense vegetation colonize and help containing sediment. Except the class change type bare ground to low vegetation, the slope in other class change types cannot separate erosional and depositional objects clearly.
Figure 34. Statistic of slope for depositional and erosional objects in each class change type

Then, for each class change type, the statistic information of the TWI was also calculated for depositional and erosional objects separately. Figure 35 illustrates the distribution of slope for depositional and erosional objects in each class change type. For the class change type low vegetation to bare ground and bare ground to low vegetation, the variable TWI can fully separate erosional and depositional objects. Erosion occurred at the place with small TWI in both class change type and deposition was the opposite. For the other three class change types, the variable TWI did not fully separate depositional and erosional objects. However, the first quartile of the TWI for depositional objects is bigger than the third quartile of the TWI for erosional objects, so TWI can separate at least 75% of the erosional and depositional objects.
6.5 Summary

Based on the object-oriented classification results for 2015 and 2016, this chapter applied the post-classification technique to detect how vegetation pattern changed from 2015 to 2016. The class change between 2015 and 2016 is calculated by subtracting the classification of 2015 from 2016. No change area is 3730.26.76 m² (low vegetation: 894.26 m², tall vegetation: 2524.86 m², bare ground: 344.14 m²). The largest change types are those from bare ground to tall vegetation (2775.15 m²) and from low vegetation to tall vegetation (2214.81 m²), meaning that tall vegetation sprawled and occupied large area from bare ground and low vegetation in one year. The changes from low vegetation to bare ground and from tall vegetation to bare ground are 23.95 m² and 3.34 m² respectively.
For low vegetation, 69% of the areas converted to tall vegetation and 30% of the areas remained low vegetation. For tall vegetation, 98% of the areas remained tall vegetation and only 2% of the areas converted to low vegetation. Therefore, more low vegetation converted to tall vegetation from 2015 to 2016. For bare ground, 77% and 13% of the areas converted to tall vegetation and low vegetation respectively, while only 10% of the areas remained bare ground.

The micro-topographic derived variables slope, TWI, aspect and hill-shaded map were generated. Among these four variables, aspect and hill-shaded map were derived for visual interpretation and slope and TWI were applied for analyzing the influence of micro-topography on vegetation pattern and sediment change. Combing the results for both period from 2014 to 2015 and from 2015 to 2016, the single variable slope cannot separate erosion and deposition, but the single variable TWI is capable of separating at least 75% of the erosional and depositional objects. The erosion is more likely to occur at the place with small TWI.

For the correlation between sediment change and vegetation pattern, change types of bare ground to tall vegetation and low vegetation to tall vegetation hold the most erosional objects as 84 and 51, respectively. Meanwhile, change types of no change and bare ground to tall vegetation hold the most depositional objects as 176 and 69, respectively. For change types of no change, the most depositional objects (103) are from tall vegetation, so more sediment settled in tall-vegetation area from 2015 to 2016. In addition, there are no depositional or erosional objects with the change type of tall vegetation to bare ground. Only two depositional and no erosional objects belong to the change type of tall vegetation to low vegetation.

Except the class change type bare ground to low vegetation, the slope in other class change types cannot separate erosional and depositional objects clearly. In other words, for those areas turned from bare ground to low vegetation between 2015 and 2016, the severe erosion was more
likely to occur at the place with low slope and deposition was the opposite. For the class change type low vegetation to bare ground and bare ground to low vegetation, the variable TWI can fully separate erosional and depositional objects. Erosion occurred at the place with small TWI in both class change type and deposition was the opposite. For the other three class change types, the variable TWI did not fully separate depositional and erosional objects. However, the first quartile of the TWI for depositional objects is bigger than the third quartile of the TWI for erosional objects, so TWI can separate at least 75% of the erosional and depositional objects.
Chapter 7. Conclusions and Future Work

This chapter summarizes the major findings of previous chapters and makes suggestions for future work. This dissertation provides a solution to monitor sediment change and vegetation competition based on micro-topography and terrestrial LiDAR for wetland restoration. Aiming at monitoring sediment change and vegetation competition in coastal environments, mapping high-accuracy micro-topography is the first difficulty that needs overcome. This dissertation proposes a rapid and flexible terrain mapping solution for densely vegetated coastal environment by integrating crown structure from terrestrial LiDAR with terrain samples from GPS. Based on the accurate micro-topography, this dissertation performs a multi-temporal change analysis for sediment and vegetation pattern to advance our understanding of correlation between sediment change and vegetation pattern change in coastal environments.

7.1 Summary of the Results and Conclusions

For mapping micro-topography under densely vegetated environment, this dissertation introduces a rapid and flexible terrain mapping solution by integrating crown structure from terrestrial LiDAR with terrain samples from GPS. For tall vegetation, statistical correlation between error and original DTM was applied to correct DTM. Comparing to typical usage of mean error, the terrain correction factor in tall vegetation is therefore adaptive to local terrain condition. For low vegetation, the study corrected the terrain by subtracting the correction factor 95th percentile error from the DSM elevation. The validated result in the study site demonstrated that the proposed method successfully corrected the terrain in low and tall vegetation with a higher accuracy. With the high resolution and high accuracy, the corrected DTM is a reliable data source for further coastal morphological analysis.
With the input of corrected DTMs, this dissertation applied CMA analysis to study the multi-temporal sediment change for the study site. Before the application to field data, an indoor experiment was conducted to examine the integration of terrestrial LiDAR and CMA, and the wave-induced erosion and deposition were successfully identified. When applied to the study site, CMA analysis identified erosional and depositional objects successfully, which are useful data for coastal wetland restoration.

The class change between 2015 and 2016 is calculated by subtracting the classification of 2015 from 2016. For low vegetation, 69% of the areas converted to tall vegetation and 30% of the areas remained low vegetation. For tall vegetation, 98% of the areas remained tall vegetation and only 2% of the areas converted to low vegetation. Therefore, more low vegetation converted to tall vegetation from 2015 to 2016. For bare ground, 77% and 13% of the areas converted to tall vegetation and low vegetation respectively, while only 10% of the areas remained bare ground. Therefore, the tall vegetation (Spartina alterniflora) colonized the study site better than the short vegetation (Seashore Paspalum) from 2015 to 2016. For the wetland restoration in the area with the similar environmental condition, Spartina alterniflora is a preferred choice for planting.

The micro-topographic derived variables slope, TWI, aspect and hill-shaded map were generated. Combing the results for both period from 2014 to 2015 and from 2015 to 2016, the single variable slope cannot separate erosion and deposition, but the single variable TWI is capable of separating at least 75% of the erosional and depositional objects. The erosion is more likely to occur at the place with small TWI. When integrating the class change type, TWI is a better variable to predict the erosional area for bank nourishment to improve wetland restoration. With the TWI products as an input, the predicted erosional area needs more attention and the bank nourishment is more efficient.
7.2 Suggestions for Future Work

This dissertation studied the sediment change and vegetation competition over a three-year period. The study site keeps suffering from the wave impact and the vegetation pattern is still evolving, so the continuous data collection and analysis is necessary to better understand the sediment change and the process of vegetation competition. With the additional data collection and analysis for sediment change and vegetation competition, the results will be a reliable reference for future wetland restoration. For example, when planting vegetation for coastal wetland restoration in the similar area around the Gulf of Mexico, the tall vegetation (Spartina alterniflora) can play an important role.

Limited by the scanning range of terrestrial LiDAR, the study site is focused on an artificial berm for the wetland restoration project, but upscaling is essential to apply the approach in a larger area of coastal Louisiana. However, different locations may present varied environmental conditions, so additional experiments are needed to validate the method in multiple locations. With the successful validation and large-extent data source, such as airborne LiDAR and satellite data, upscaling to larger area is feasible.
References


Vita

Xukai Zhang was born in Daqing City, Heilongjiang Province, China. He received his Bachelor of Engineering degree in Surveying and Mapping Engineering from China University of Geosciences, Beijing, China, in 2010. In the fall of 2010, he began his graduate study and earned his Master of Science degree in Cartography and Geographic Information Systems from University of Chinese Academy of Sciences, Beijing, China, in 2013. Since the fall of 2013, he has been a Ph.D. student in the Department of Geography and Anthropology, Louisiana State University, supported by a teaching assistantship and graduate assistantship and supervised by Dr. Xuelian Meng. He held an internship in the East Baton Rouge Parks and Recreation (BREC) from June to August 2016. His research interests include remote sensing, GIS and coastal morphology.