Lidar Data Collected in Marshes: Its Error and Application for Sea Level Rise Modeling

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NOAA Coastal Services Center
LINKING PEOPLE, INFORMATION, AND TECHNOLOGY

2234 South Hobson Avenue
Charleston, South Carolina 29405-2413
(843) 740 -1200
www.csc.noaa.gov

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Introduction

The improvements to bare earth digital elevation models (DEMs) that have been realized in coastal areas from the application of lidar data (Figure 1), as well as the common availability of these data, are among the factors that have led to an increased belief and trust in lidar as an elevation layer (Franklin, 2008). Marsh vegetation, however, is very difficult to penetrate (Rosso and others, 2003), and elevation errors can be dramatically different from adjacent uplands and from those often quoted in accuracy reports. This leads to a poor estimation of the lidar accuracy in marshes and to the potential overuse or misuse of the data. Lidar collection in marshes occurs in nearly all coastal data collections, and with increased efforts to distribute the data, the data are used for a wide variety of applications, some valid, some may be less so. For example, sea level rise and inundation models are incorporating lidar data, and much of the dramatic change occurs in marshes. Therefore, there are real needs to define elevation accuracies in these habitats and, if possible or necessary, improve the data to support realistic scenarios of small scale water level changes (Schmid and others, 2009).

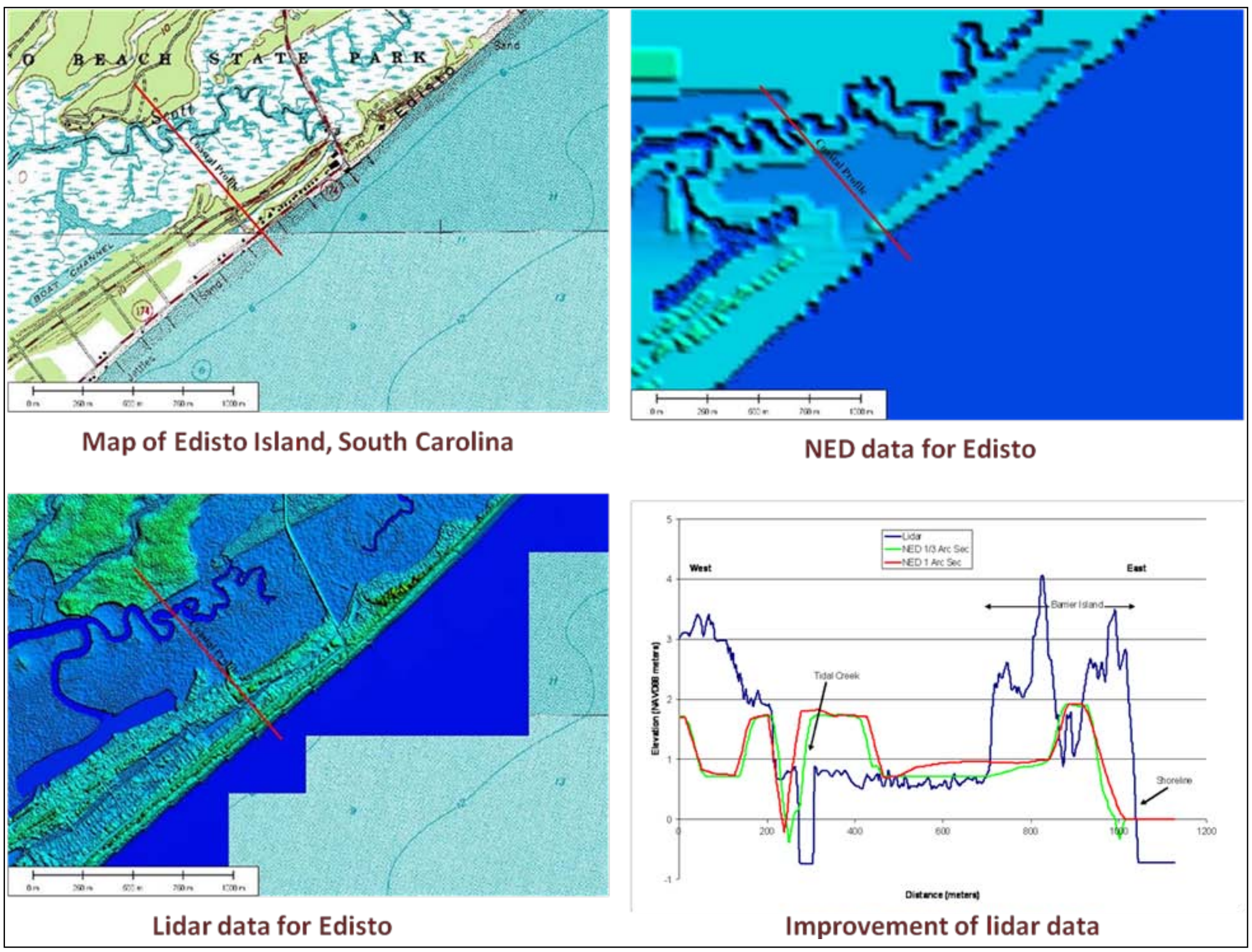


Figure 1. Lidar and National Elevation Data (NED) Comparison in Edisto, South Carolina. A coastal profile (red line) across the upland-marsh barrier island is used to compare data from the NED and more recent lidar data. The profile comparison highlights the differences and the increased accuracy and resolution of the

lidar data in this coastal setting. The NED (either 1 arc second or 1/3 arc second) do not accurately portray the barrier island, marsh surface, or upland elevations.

This paper will examine the native accuracy of, corrective techniques to, and associated use of lidar data in coastal settings, particularly marshes, for sea level rise studies. Sea level rise studies can take many forms; however, this paper will concentrate on the use of lidar data in a habitat migration model. The Sea Level Affecting Marshes Model, or SLAMM (Clough, 2008), was chosen since it is one of the most commonly used. This model has been applied to coastal areas throughout the U.S. using moderate-resolution elevation data (i.e., National Elevation Dataset) (Craft and others, 2009) and, more recently, at specific coastal sites using lidar data. The techniques described are not intended to be uniformly applicable to all models, but understanding the limitations of lidar in these environments may be beneficial for many types of sea level rise studies. It is simply assumed that the quality and accuracy of information output from the model is related to the accuracy of the data used in the model.

The SLAMM model itself is under constant development. The full discussion of the model, its merits, and its drawbacks is beyond the scope of this report (see for example Scarborough and others, 2009); however, its dependence on elevation data is highlighted as an example of the need for correct coastal elevations. Elevation and its derivative (slope) are two of the primary data sets used to run the model; the third is the wetland land cover derived from base land cover data sets (e.g., National Wetlands Inventory, Coastal Change Analysis Program).

Applications of Lidar in Marshes

The use of lidar to study natural resource evolution is expected to increase in the future (Cary, 2009) as more data are collected and shared among organizations. Modeling software (e.g., Sea Level Effecting Marshes Model) is accepting higher resolution data (e.g., lidar), and software products have become more user-friendly (Franklin, 2008). In many cases, these developments have provided better insights and increased confidence in model results (i.e., improvements in resolution). The increased use of lidar, however, places an increased reliance on lidar's absolute accuracy, and results can be misleading in areas where the performance of the technique is less optimized, such as marsh habitats.

Some of the more common marsh applications using lidar include single surface (bath-tub) sea level rise inundation models and invasive species mapping, along with restoration planning tools such as SLAMM and the Marsh Analysis and Planning Tool Incorporating Tides and Elevations, or MAPTITE (NGS, 2009). The purpose of this group of applications and tools is to provide some guidance on where wetland species will thrive or how they will change in the future, based largely on the substrate elevation and changes in water levels. These applications do not typically have direct human safety implications; however, the results do have financial, planning, and protection consequences.

Measured Lidar Accuracy in Marshes

Several marshes in the Charleston, South Carolina, area were surveyed to understand the difference between the "real" marsh elevations and the lidar-generated ones. The survey data were compared with the lidar surfaces (i.e., DEMs), and differences in elevation were used to define the accuracy and character of the lidar collection. Ground control points (GCPs) were collected in marshes and in upland areas using Global Positioning System (GPS) and traditional surveying methods. Vegetation density, height, and types were also measured at the GCPs in the marsh to assess the correlation to different marsh environments.

To test the vertical accuracy of the lidar, a 2-meter "bare earth" DEM was generated using an Inverse Distance Weighted (IDW) technique with the as-received bare earth classified lidar points. Since the data are being used in a regional model (i.e., the model inputs are not marsh-vegetation specific), this report will focus on the general accuracy and character of the lidar data and their use in the sampled marshes as a whole.

Comparison of Marsh Points to Reported Accuracy

The confidence in the lidar data for specific applications depends on each data set's vertical accuracy statistics in any number of land cover classes (Table 1; Figure 2). In many cases the data are tested in five upland land cover classes: Open Terrain, Forest, Weeds/Crops, Scrub/Shrub, and Built-Up (Urban) settings. Data properties in the Open Terrain class are commonly used to define the overall quality of the data collection and processing. The other classes help to define the data classification quality and character (i.e., filtering and removal) of points falling on vegetation or structures for a bare earth surface.

Table 1. Accuracy Assessment Values for Charleston Data Set

Land Cover	# of Points	$RMSE_z$ (m)	Mean (m)	Vertical Accuracy (m)
All	75	0.0934	-0.019	0.183
Open Terrain	26	0.0921	-0.0275	0.1805
Forest	18	0.1072	-0.0609	0.2101
Weeds/Crops	11	0.0755	0.0112	0.1479
Scrub/Shrub	9	0.1029	0.0629	0.2017
Built-Up	11	0.079	0.028	0.1548

For work in a particular land cover, the supplemental accuracy (i.e., the accuracy within each class) can be used to define the data quality and properties. Often there is no marsh category, so the closest approximation may include the Weeds/Crops and Scrub/Shrub categories. In this case, the accuracy of the base data (Table 1, RMSE, or root mean square error) is similar across all categories, including the weeds and scrub categories. Plots of point errors (Figure 2) highlight the trends for each category and depict the overall positive bias (lidar derived elevation above actual) for the weeds and scrub categories. Using Scrub/Shrub as an analog for marsh, one may expect that the vertical accuracy of the data in marshes is approximately 20 centimeters (95% confidence; RMSE of 10 centimeters) and that the data are slightly positively biased by about five centimeters (Table 1, Mean). This is important information for the use of the data but is only an approximated value, since it is based on related land cover information and not specifically measured in marshes.

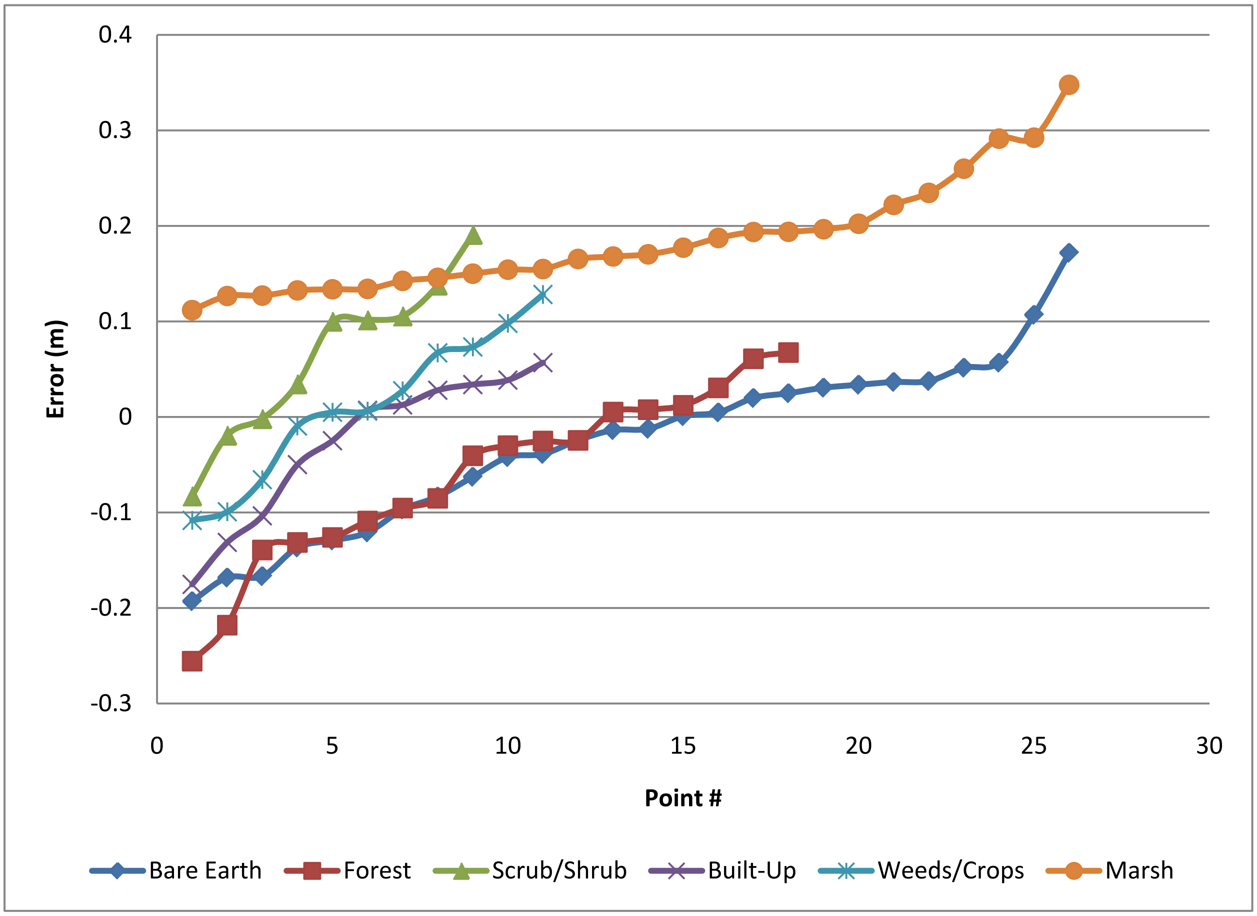


Figure 2. Sorted Errors with Random Selection of Marsh Points

When testing the marsh category separately, it becomes clear the marsh land cover is a unique category that may have significantly higher errors and biases than the "upland" (i.e., traditional) land covers (Figure 2). The accuracy values based on GCPs collected in the marsh for the study area (Table 2) highlight the difference from upland accuracy. The vertical error (RMSE) for Marsh is more than twice the tested value of the data set. More importantly, however, the Mean elevation is over 15 centimeters above the actual bare earth elevation. This suggests that the lidar data are highly positively biased in marsh land cover. Any model results or information generated from the lidar data in marshes have the potential to be systematically biased compared to upland areas.

Table 2. Marsh Land Cover Accuracy Specifications Compared to Upland Consolidated Accuracy

Land Cover	# of Points	RMSE (cm)	Mean (cm)	Standard Deviation (cm)	Accuracy Z (cm)
Upland	75	9	-2	9	18
Marsh	224	23	15	18	46

Discussion and Model Results

The errors and biases highlighted above, as well as depicted in other studies (Rosso and others, 2006; Populus, 2001; Sadro and others, 2007) document the error in assuming that lidar accuracy in marshes is the same as in upland land covers, where accuracy testing commonly takes place. Compounding this problem is the fact that in marshes, the subtle microtopography has increased importance as small differences in elevation can lead to large changes in flooding frequency and the types of species that inhabit and flourish in the area (Morris and others, 2005; Montane and others, 2006). Thus, the problem of modeling the effects of sea level rise in marshes, for example, becomes even more exaggerated.

There is promise for future improvement with many works on this issue and a high level of interest in lidar-derived elevations for sea level change (CCSP, 2009). Waveform data from the lidar pulses is one future improvement that may help in marsh habitats (Wagner et al 2004; 2007). The present and most common method of lidar collection and data storage, however, limits the user's ability to process raw lidar wave forms (i.e., waveform digitization) in marsh vegetation separately or with a unique filter. The software and experience needed to perform these operations is coming but at present is not the common practice (Franklin, 2008).

Lidar Limitations

The essence of the problem is illustrated in Figure 3. The lidar ground points (purple) in this *Spartina*-dominated marsh are nearly uniformly above the ground surface (green points in Figure 3 insert). The lidar points, while below the middle of the vegetation (yellow points; Figure 3 insert), do not represent the ground surface. It is interesting to note that about 99% of the points in this marsh were considered ground points and nearly all points are single returns (i.e., 1 of 1), even though the marsh vegetation was consistently over 1 meter in height (red point; Figure 3 insert).

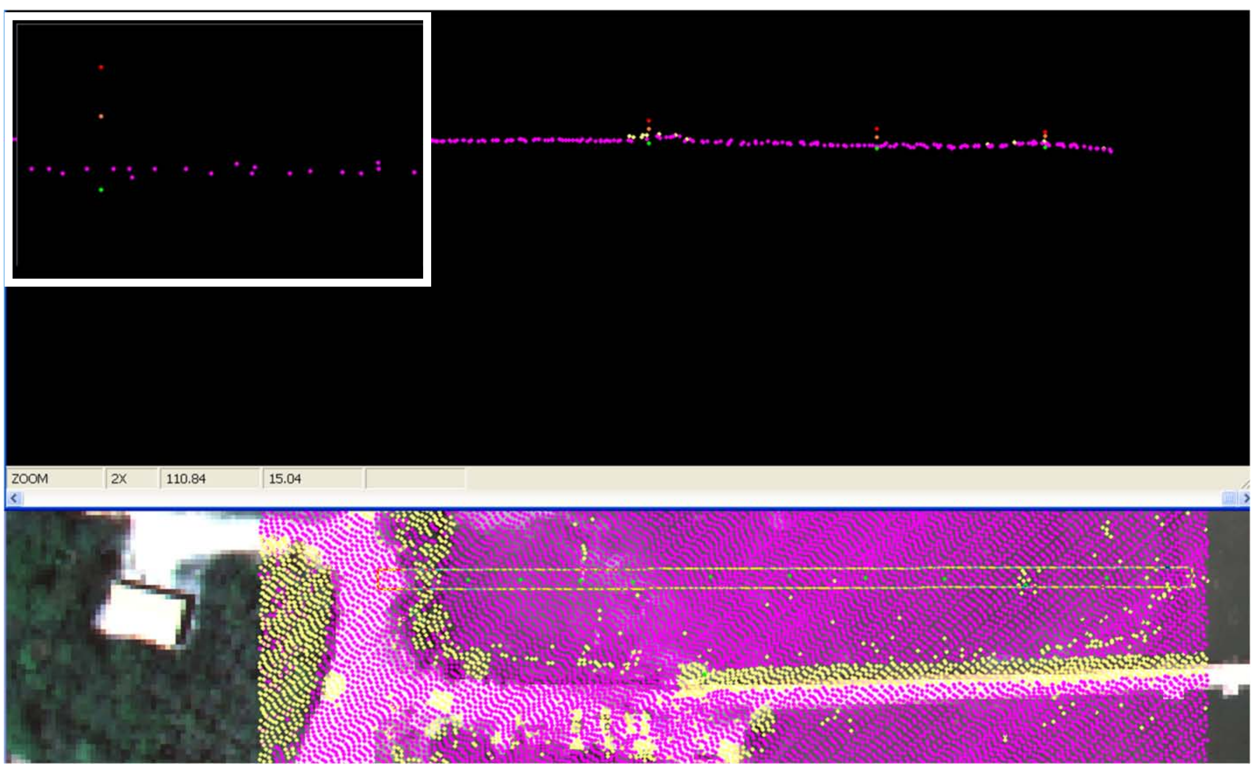


Figure 3. Profile through *Spartina*-Dominated Marsh. Pink points are ground classified lidar points; yellow points are unclassified lidar points; green points are ground GCPs; orange points are middle vegetation; and red points are tops of vegetation. The insert is a magnified example of one GCP location.

The lack of "real" bare earth points is the essence of the problem and likely a product of the resolution of lidar and selection of discrete return triggers in the reflected waveform (Wagner and others, 2007; Wagner and others, 2004). The diffuse returns from erectifile marsh vegetation, coupled with saturated soils, can create an ambiguous return, making it difficult for the lidar sensor to resolve the correct elevation.

Building a Custom DEM

To goal of this process is to improve accuracy by reducing the bias. To do so, we explored some fairly common techniques to generate improved DEMs for marsh-specific applications. The emphasis here is placed on bare-earth surfaces, but similar techniques can also be used to produce a first-surface or vegetation-height digital surface model (DSM). The points from the as-received lidar data can be used, modified, selected, or segregated to improve the end result. It should not be assumed that the final or as-received product is the optimal one for all uses (Franklin, 2008; Maune and others, 2007).

For SLAMM, the DEM is a critical input. DEMs, however, are not all generated the same way, nor does their creation adhere to one specific standard (Maune and others, 2007). Generation of a DEM is a step that is also a user-defined variable. Creating the best DEM for a specific use requires knowledge of the data, the application, and the terrain being studied. The art of DEM generation from lidar data has traditionally had several common routes (i.e., TIN, IDW, and binning) and some "designer" techniques (e.g., kriging, splines, decimation, breaklines). Less common techniques are employed in situations where the data do not meet the user needs (e.g., not bare-earth filtered), require additional information (e.g., hydro correction), or have specific collection properties that do not adhere to generation of a typical lidar surface (e.g., low point density) (Maune and others, 2007).

DEM Variation

A DEM can be generated from points in many ways, with the choice of interpolation and gridding routines and varying resolution being the most common differences (Maune and others, 2007). These will be the focus for generation of a better DEM in marsh areas. Marsh elevations do not typically change dramatically over small spatial scales, except near tidal creeks, which allows some latitude in varying the DEM resolution. For example, a 4 or 6 meter DEM can, in most cases, provide the same level of information as a 1 or 2 meter DEM in flat areas (Maune and others, 2007). An important consideration is the extent of the DEM beyond the marsh and the importance of upland feature definition. Where discontinuous marsh is present or where upland areas dominate, the more involved technique of customized point classification (i.e., filtering) may be a better option than varying DEM generation.

Previous works (Rosso and others, 2003; 2006) have documented only minor improvements using different deterministic (IDW) and geostatistical (Kriging) interpolation models, with high density lidar data (>0.5 points/meter). As a result, a different direction was chosen that employed a simple "bin" type gridding process. The binning method is fundamentally different in that it subsets the data by each grid cell. The value of the grid cell (i.e., the DEM value) can be chosen to represent the average, minimum, maximum, or nearly any statistic from the points (i.e., subset) within each cell. Unless the cell contains only one point or all the points are exactly the same, the cell value is not likely to represent each point, and thus there is typically a loss of some information. For example, if a 10 meter x 10 meter grid contains 50 points, and only the minimum point is used to represent the cell's value, 49 points are not represented. This approach is, however, consistent with the overall goal of filtering, as long as the parameters are chosen correctly. In the case of the marsh, some (i.e., most) points must be removed to better model the actual surface if most are actually above the ground surface.

Minimum Bin Method

The minimum bin technique simply selects the lowest point in the cell to represent the grid or raster value. In the case of a cell size at the native resolution, the value would be the value of the single point; as the cell size increases, the deviation of the value from the selection of a single point will likely increase. As such, varying resolution is the primary parameter to control the surface; increasing or decreasing the cell size will produce surfaces with different elevation characteristics (Figure 4). In this study, the minimum bin technique was applied, using various resolutions (i.e., grid sizes), to the different marsh habitats and the data analyzed to arrive at a “best fit” resolution. The same technique has been used in other studies (Rosso and others, 2003) and has reduced vegetation errors, but in open areas (e.g., mudflats) can produce DEM values that are lower than actual ground elevations (i.e., negative bias). Thus, each type of marsh, specific marsh location, or the intended use of the DEM, may have its own “target” resolution.

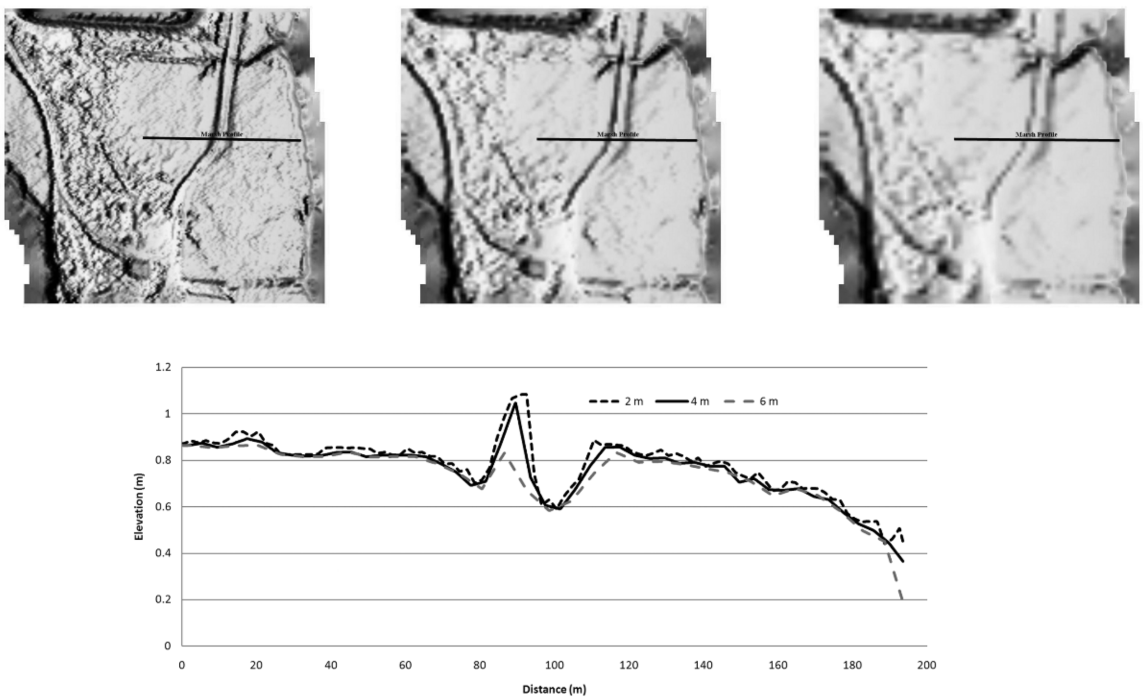
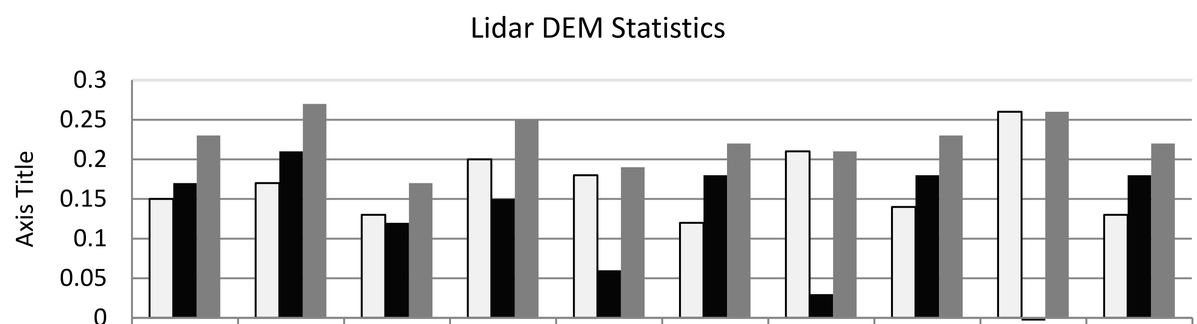


Figure 4. . DEMs Generated from Varying Bin Resolutions of 2, 4, and 6 Meters from Left to Right and the Associated Marsh Profiles. The progression shows a decrease in resolution but also a removal of apparent high values caused by vegetation. The 4-meter DEM appears to be the best resolution for this location.

Results of Minimum Bin DEM Variation

The results at one marsh site from varying the DEM (Figure 5) resolution and using two different techniques highlight the improvements that are possible. The minimum bin technique was compared to the IDW technique, which is a common and appropriate (Rosso, and others, 2003; Maune and others, 2007) technique for DEM generation from lidar. The minimum bin technique produced lower RMSE and bias results in all but the 10-meter case. In nearly all DEMs the lower resolution grids had lower RMSEs than the standard 2-meter IDW DEM (Figure 5). This example marsh had a dominance of *Spartina*, which is also the most common vegetation in the study.



	2m-min	2m-idw	4m-min	4m-idw	6m-min	6m-idw	8m-min	8m-idw	10m-min	10m-idw
□ STD	0.15	0.17	0.13	0.2	0.18	0.12	0.21	0.14	0.26	0.13
■ Bias	0.17	0.21	0.12	0.15	0.06	0.18	0.03	0.18	-0.01	0.18
■ RMSE	0.23	0.27	0.17	0.25	0.19	0.22	0.21	0.23	0.26	0.22

Figure 5. Results of Lidar DEM Variation

In the example marsh, it appears that the 4-meter bin size (i.e., 4m-min) is the most appropriate. When this same process is performed at a marsh dominated by *Juncus romaniarus*, however, the results are somewhat different. In the case of *Juncus*-dominated marsh, the best results were from a minimum bin size of 10 meters. The ideal solution would probably be to define the minimum bin size for the vegetation type, densities, and heights. In most cases, however, this exceeds the amount of information collected at a site.

DEM Generation

Given that the sites within the study area comprise a mix of the various vegetation types and cover a large area, a 5-meter resolution DEM using the minimum bin technique described above was generated (Figure 6). The overall accuracy was tested using the marsh points collected in this study, as well as previously collected upland points for the area, to assess the overall application of the generated DEM in models that incorporate both upland and marsh elevations (e.g., SLAMM, storm surge mapping). Using a grid larger than 5 meters begins to oversmooth the upland features in the DEM (see Figure 4) and may compromise overall performance (i.e., working against the intended goal) in smaller or complex marsh areas.

Figure 6. A 5-Meter DEM Generated Using Minimum Bin Technique

As expected in the marsh areas, the DEM derived from a minimum bin technique was less biased (Table 3, Mean) than the conventional DEM and had a lower RMSE. In this respect the technique proved reasonable; however, it may have suffered in areas near tidal streams or in areas of steeper slopes. In the upland areas, using previously defined points as control (NOAA Coastal Services Center, 2007), the RMSE and bias were greater in the 5-meter bin method than the baseline TIN method (Table 3). The RMSE value is acceptable (i.e., 18 centimeters would nearly meet the collection specifications); however, the data are biased (i.e., the DEM is lower than control points) by about 11 centimeters. In most upland locations, this is probably not a problem, but flat low-lying upland areas adjacent to wetlands may be sensitive to this offset.

Table 3. Error Comparison between DEM Types

		RMSE	Mean	STD
Upland	TIN	0.088	0.006	0.088
	5m Bin	0.182	-0.113	0.143
Marsh	TIN	0.233	0.153	0.176
	5m Bin	0.156	0.032	0.153

Application of the Vegetation Adjusted DEM in SLAMM

SLAMM Runs

SLAMM (version 5.01) was run for the greater Charleston, South Carolina, area using the as-received and minimum bin DEMs. The tidal, erosion, and accretion model parameters and input land cover data set were held constant in all runs. The tidal data for the runs were taken from the Charleston tide station, and default vertical wetland accretion (~ 2 millimeters/year) and horizontal erosion parameters (~ 1 meter/year) were used because of the size and complexity of the study area. The 1-meter sea level rise by 2100 scenario was chosen based on recent (Fletcher, in press) sea level information. Land cover was based on the 1984 National Wetland Inventory (USFWS, 2009). The model was run for two dates: 2025 and 2050. Lastly, it was assumed that developed upland areas (e.g., City of Charleston, North Charleston) would be protected, so developed areas were not allowed to change to wetlands. More information on the SLAMM model and the specific parameters is available at *www.warrenpinnacle.com/prof/SLAMM/index.html*.

A 5-meter resolution DEM was deemed acceptable for this application since the other primary data source (NWI data) has a lower resolution than 5 meters. The 5-meter minimum bin (Figure 6) and resampled 5-meter DEMs derived from a TIN were run to predict land cover changes for 2025 and 2050 under the 1-meter by 2100 sea level rise scenario. The initial and 2050 values are shown in Figure 7. This time period represents a total of 47 centimeters of sea level rise. Again, the premise behind the comparison is that the accuracy of the data used in the model has a direct result on the quality of the information provided.

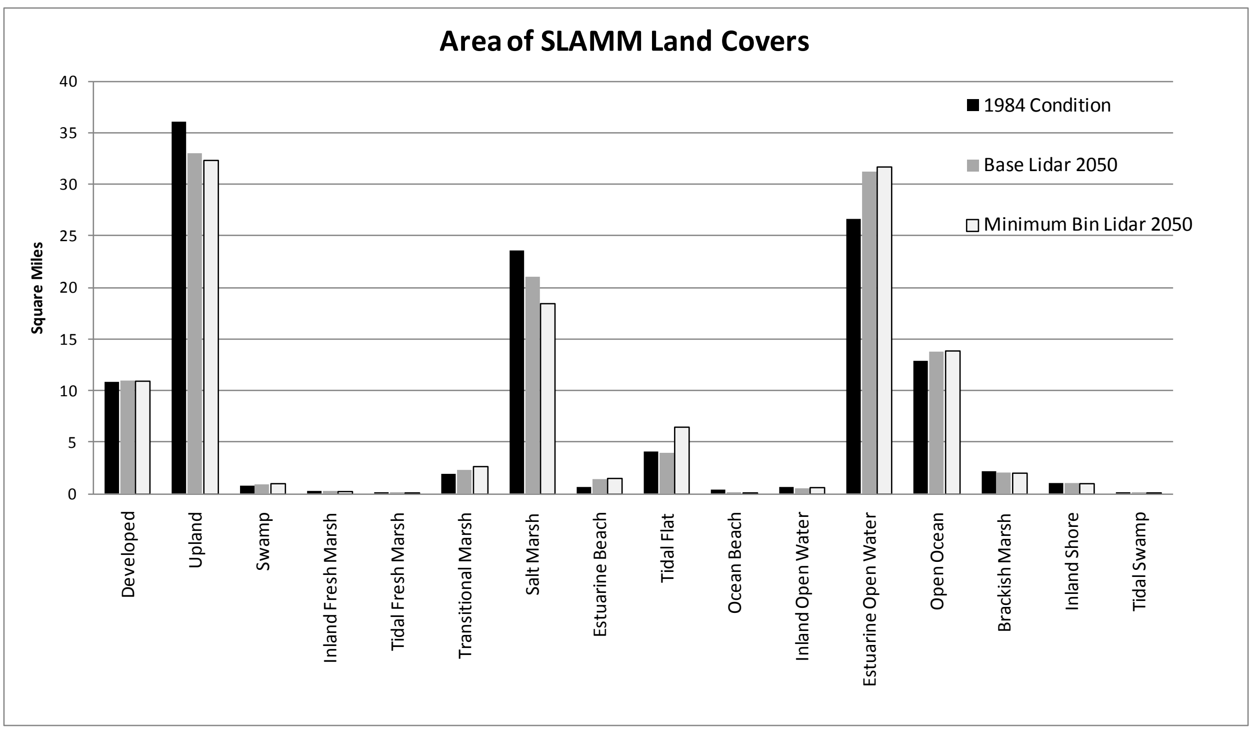


Figure 7. Changes from the Initial Condition to the Predicted 2050 Period Using the Base Lidar (TIN) and the Corrected DEM

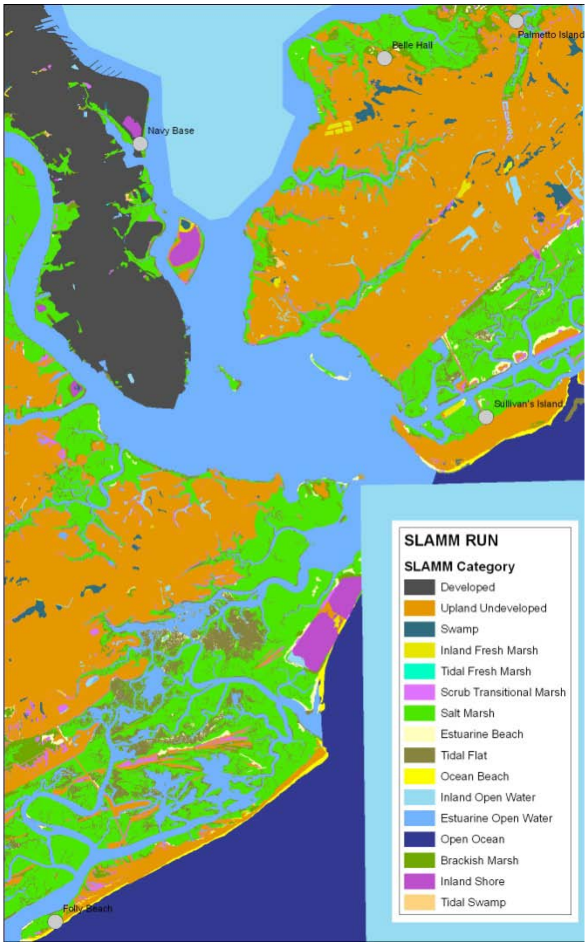
The major area changes from the initial condition to the 2050 period in both the base lidar and minimum bin runs are in the upland, salt marsh, tidal flat, and estuarine open water categories (Figure 7). The largest differences between the two DEMs within these high-change categories are in the salt marsh and tidal flat land covers (Figure 7 and Table 4). The large differences between the two DEM runs in these land covers highlight the sensitivity of the model to changes in the marsh elevations.

Table 4. Modeled 2050 Changes in % of the Initial Land Cover Area and the Difference between the Two DEMs

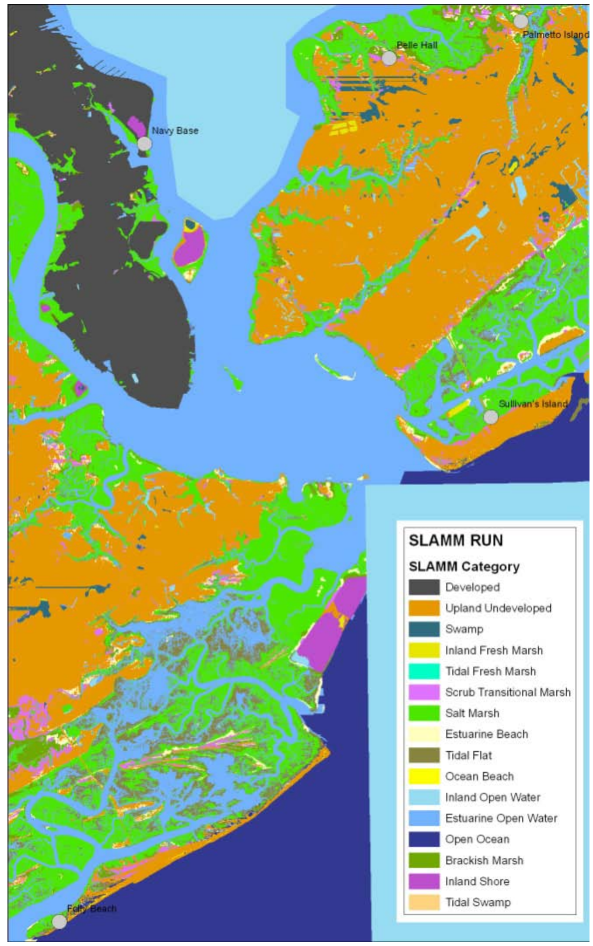
SLAMM Land Cover	Base Lidar DEM	Corrected DEM	Difference
Developed	0%	0%	0%
Upland	-8%	-10%	27%
Swamp	15%	12%	-21%
Inland Fresh Marsh	-15%	-23%	54%
Tidal Fresh Marsh	-55%	-61%	11%
Transitional Marsh	23%	41%	76%
Salt Marsh	**-11%**	**-22%**	**101%**
Estuarine Beach	100%	111%	12%
Tidal Flat	**-6%**	**54%**	**-1018%**
Ocean Beach	-89%	-85%	-5%
Inland Open Water	-21%	-14%	-34%
Estuarine Open Water	17%	19%	10%
Open Ocean	7%	7%	3%
Brackish Marsh	-6%	-10%	62%
Inland Shore	-1%	0%	-86%
Tidal Swamp	-63%	-71%	14%

The results in Table 4 detail areas of high change and how much difference there is between the two DEM model runs. For example, there is an 11% loss of salt marsh by 2050 using the as-received DEM in the model, but a 22% loss of salt marsh using the minimum bin DEM. The differences between the two model runs in the tidal flat and salt marsh land covers is notable with the as-received DEM model predicting a decrease in tidal flat and the minimum bin DEM model predicting an increase. This suggests that a larger percentage of salt marsh is being converted to tidal flat in the minimum bin DEM run than in the as-received DEM run.

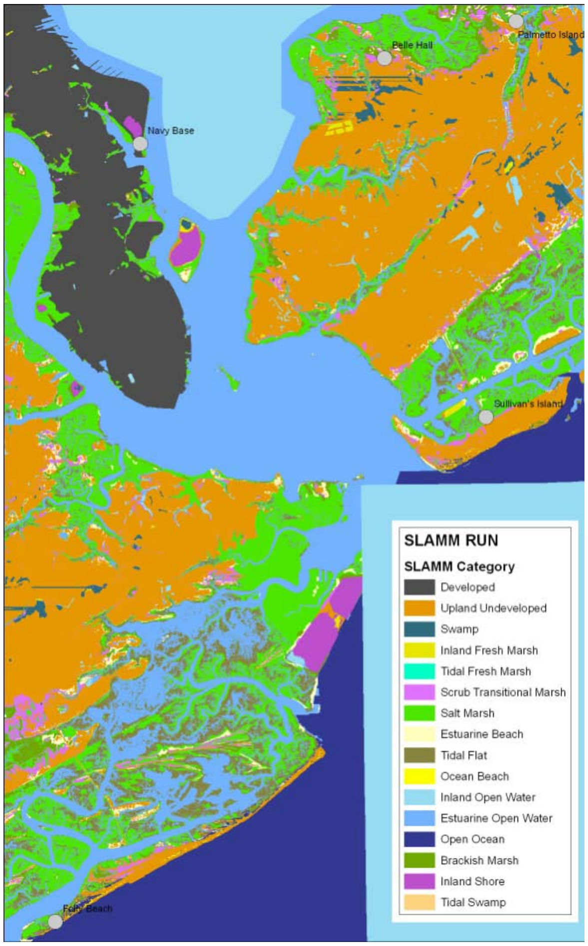
In a regional sense, the runs appear to be reasonable (Figure 8) with no major inconsistencies (e.g., large areas that have different land covers) noted between the models using the two different DEMs. The overriding differences in the model outputs in marshes (Table 4) are difficult to see at a regional scale (Figure 8) and are better represented at some of the specific study sites (Figure 9).



A. 1984 Baseline



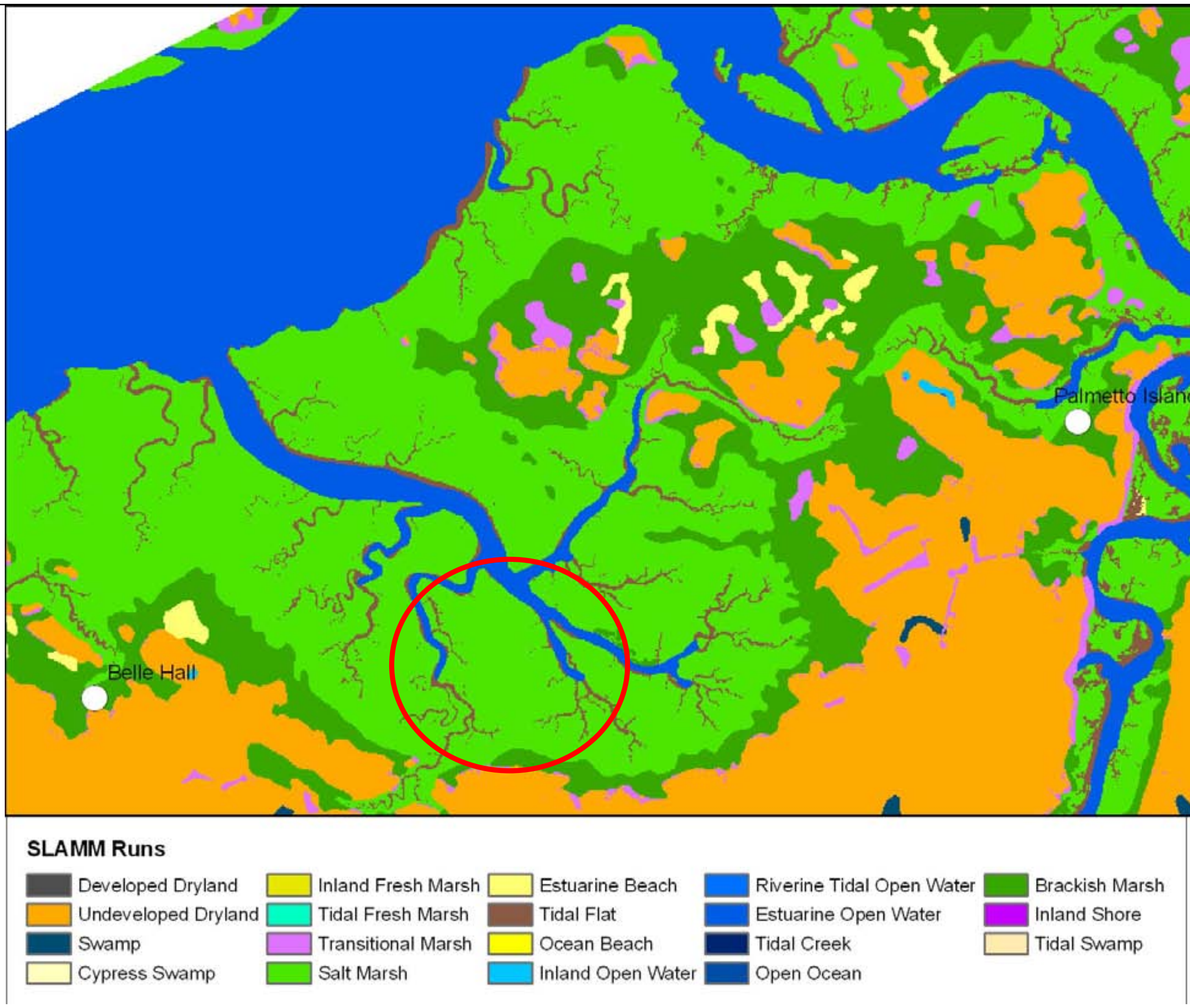
B. 2050 Base Lidar DEM



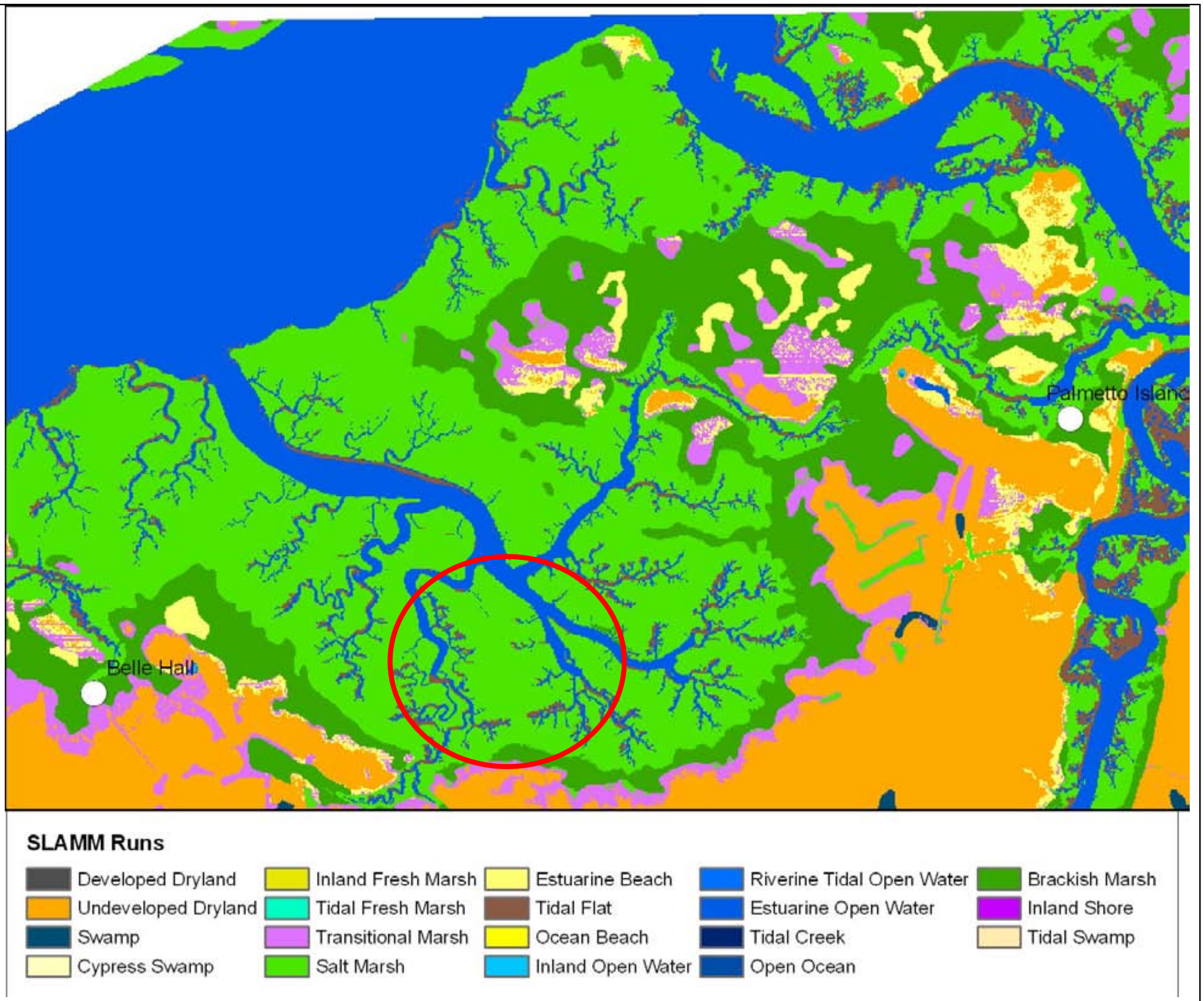
C. 2050 Corrected Lidar DEM

Figure 8. SLAMM runs for Charleston, South Carolina

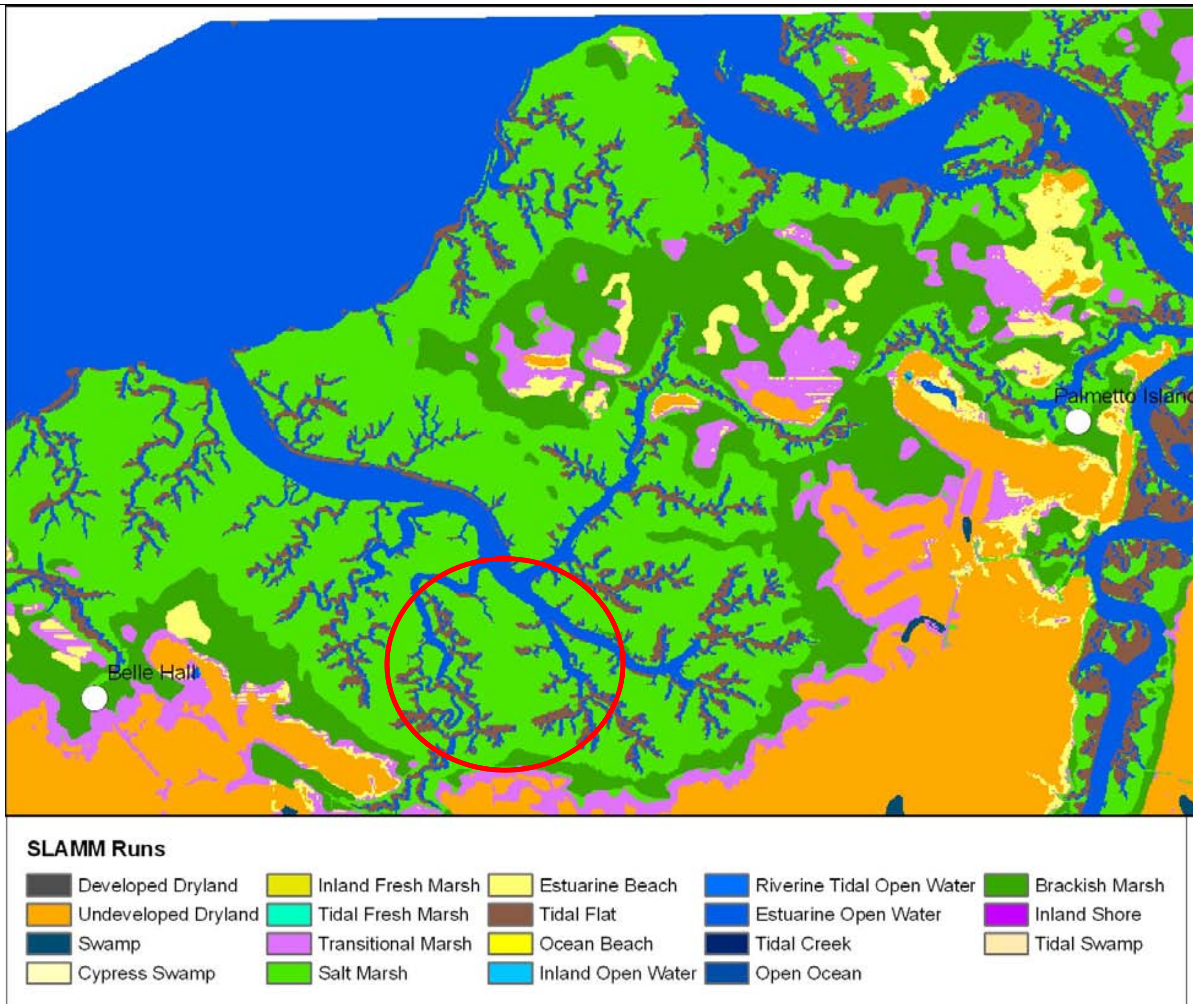
The major difference previously noted is the loss of marsh to tidal flat. At the combined Palmetto–Belle Hall location (Figure 9A-C) it is evident that one of the differences is in the amount of modeled tidal flat area adjacent to stream channels (red circles in Figure 9A-C). In the as-received DEM 2050 run (Figure 9B) there is little additional tidal flat (brown color) adjacent to channels (blue); in fact, some of tidal flat initially present is lost to water (blue) without any accompanying change in the adjacent marsh to tidal flat (i.e., there is no migration of tidal flat to a higher elevation). In the minimum bin DEM run, however, the loss of tidal flat to water is accompanied by the creation of additional tidal flat adjacent to the channels (i.e., the tidal flat habitat migrates onto the marsh surface).



A. 1984 Initialization SLAMM Output



B. 2050 SLAMM Output Using As-Received Lidar DEM



C. 2050 SLAMM Output Using Minimum Bin Lidar DEM

Figure 9. SLAMM Outputs for the Palmetto–Belle Hall Area

This specific example appears to highlight the removal of vegetation adjacent to tidal creeks where plant heights are typically taller and vegetation denser. These types of areas tend to be more difficult for the lidar to penetrate and commonly result in anomalously high elevations. The result from the minimum bin DEM (Figure 9C) is not being presented as "correct," but the effects of 47 centimeters of sea level rise without an appreciable increase in sedimentation (i.e., accretion) would be expected to cause some migration and a potential expanse of tidal flats in areas near small tidal creeks.

The SLAMM outputs (Figures 7, 8, and 9) and trends (Table 4) highlight the importance and sensitivity of elevation data for sea level rise modeling. In the lower, more affected areas (i.e., marshes) the difference in the change between 1984 and 2050 using DEMs generated from the same points with different surface generation techniques was dramatically different. The run using the minimum-bin-generated DEM had twice as much predicted marsh loss and ten times more tidal flat than the run using the as-received DEM. This is just one example of the effects of using a 'corrected' DEM in modeling future conditions. Higher resolution studies, for example determining hydro-periods, may have even more sensitivity to the correct marsh elevations (Eaton and Yi, 2009).

An Improved DEM Is Possible

The overarching messages are as follows:

1) It should not be assumed that the “best” surface has necessarily been produced or delivered from the vendor or supplier;
2) Elevation values from lidar data can be biased in marsh type vegetation;
3) The lidar data can be improved for marshes and densely vegetated areas using varying DEM generation techniques and classification levels; and
4) These improvements are realized in common modeling applications.

A few of the options for generating an improved DEM in marshes have been reviewed, but they are by no means the extent of possibilities; rather they are some of the simpler techniques and can be implemented by either end users or producers.

The type of algorithm, bin sizes, and bin types and the amount of effort needed to generate meaningful improvements to the DEM will depend on a number of factors. The important factors include the vegetation types, species variations, and vegetation heights at the time of data collection, the topographic complexity of the marsh, the size and spatial complexity of the marsh, and ultimately the level of accuracy that is needed in the application. The example using SLAMM required less resolution; however, a more site-specific model such as MAPTITE or the need for a higher-resolution site-specific DEM may benefit from the improved customization possible using specific classification techniques.

References

Cary, Tina. 2009. “New Research Reveals Current and Future Trends in Lidar Applications.” *Earth Imaging Journal*. Earthwide Communications. Accessed at *www.eijournal.com*.

Climate Change Science Program (CCSP). 2009. *Coastal Sensitivity to Sea-Level Rise: A Focus on the Mid-Atlantic Region.* A report by the U.S. Climate Change Science Program and the Subcommittee on Global Change Research. James G. Titus (Coordinating Lead Author), Eric K. Anderson, Donald R. Cahoon, Stephen Gill, Robert E. Thieler, Jeffress S. Williams (Lead Authors). U.S. Environmental Protection Agency. Washington D.C. 320 pages. Accessed at *www.gcrio.org/orders/product_info.php?products_id=239*.

Clough, J., and R. A. Park. 2008. “Sea Level Affecting Marshes Model, Version 5.01.” Warren Pinnacle Consulting and Eco Modeling. Software available at *www.warrenpinnacle.com/prof/SLAMM/index.html*.

Craft, C., J. Clough, J. Ehman, S. Joye, D. Park, S. Pennings, H. Guo, and M. Machmuller. 2009. “Effects of Accelerated Sea level Rise on Delivery of Ecosystem Services Provided by Tidal Marshes: A Simulation of the Georgia (USA) Coast.” *Frontiers in Ecology and the Environment*. Volume 7, Issue 2. Pages 73 to 78.

Eaton, T. T., and C. Yi. 2009. “Hydroperiod and Hydraulic Loading Treatment Potential in Urban Tidal Wetlands.” *Hydrology and Earth System Sciences Discussions*. Volume 6. Pages 589 to 625, Accessed at *www.hydrol-earth-syst-sci-discuss.net/6/589/2009/*.

Fletcher, C.H., 2009. “Sea level by the end of 21st century: A review.” In press, *Shore and Beach*. Volume 77, Number 4. Pages 4 to12.

Franklin, Rod. 2008. “Lidar Advances and Challenges: A Report from the International Lidar Mapping Forum.” *Imaging Notes Magazine*. Accessed September 2009 at *www.imagingnotes.com/go/article_free.php?mp_id=129*.

Maune, D., S. M. Kopp, C. A. Crawford, and C. E. Zervas. 2007. “Introduction: The DEM Users Manual.” In D. Maune, editor, 2007, *Digital Elevation Model Technologies and Applications: The DEM Users Manual*, 2nd edition. Bethesda, Maryland. American Society for Photogrammetry and Remote Sensing.

Montane, Juana M., and Raymond Torres. 2006, “Accuracy Assessment of Lidar Saltmarsh Topographic Data Using RTK GPS.” *Photogrammetric Engineering and Remote Sensing*. Volume 72, Number 8. Pages 961 to 967.

Morris, J.T., D. Porter, M. Neet, P. A. Noble, L. Schmidt, L. A. Lapine, and J. R. Jenson. 2005. “Integrating LIDAR Elevation Data, Multi-Spectral Imagery, and Neural Network Modeling for Marsh Characterization.” *International Journal of Remote Sensing*. Accessed at *www.tandf.co.uk/journals*.

National Geodetic Survey (NGS). 2008. “Guidelines for Establishing GPS Derived Orthometric Heights.” NOAA Technical Memorandum NOS NGS 59.

National Geodetic Survey (NGS) and Center for Operational Oceanographic Products and Services (CO-OPS), 2009. “Marsh Analysis and Planning Tool Incorporating Tides and Elevations (MAPTITE).” Beta Version.

National Oceanic and Atmospheric Administration (NOAA), Coastal Services Center. 2008. “Lidar Quality Assurance and Quality Control Report for Colleton and Charleston Counties, South Carolina.” NOAA Coastal Services Center. Available at *ftp://ftp.csc.noaa.gov/pub/crs/beachmap/qa_docs/sc/charleston_colleton*.

Populus, J., G. Barreau, J. Fazilleau, M. Kerdreux, and J. L’Yavanc. 2001. “Assessment of the Lidar Topographic Technique over a Coastal Area.” In *Proceedings of CoastGIS 2001, 18-20 June, Halifax, Canada*. Accessed at *www.coastgis.org/01pdfs/populus.pdf*.

Rosso, P. H., S. L. Ustin, and A. Hastings. 2003. “Use of Lidar to Produce High Resolution Marsh Vegetation and Terrain Maps.” Three Dimensional Mapping from InSAR and LIDAR Workshop. June 17-19. International Society for Photogrammetry and Remote Sensing. Portland, Oregon.

Rosso, P. H., S. L. Ustin, and A. Hastings. 2006. “Use of Lidar to Study Changes Associated with *Spartina* Invasion in San Francisco Bay Marshes.” *Remote Sensing of Environment*. Volume 100. Pages 295 to 306.

Sadro, S., M. Gastil-Buhl, and J. Melack. 2007. “Characterizing Patterns of Plant Distribution in a Southern California Salt Marsh Using Remotely Sensed Topographic and Hyperspectral Data and Local Tidal Fluctuations.” *Remote Sensing of Environment*. Volume 110. Pages 226 to 239.

Scarborough, R. W. 2009. *Application of the Sea Level Rise Affecting Marsh Model (SLAMM) Using High Resolution Data at Prime Hook National Wildlife Refuge*. Accessed August 2009 at *www.swc.dnrec.delaware.gov/coastal/Documents/PHNWR%20SLAMM.pdf*.

Schmid K., B. Hadley, R. Mataosky, R. Love, and R. McGuinn. 2009. “Processing and Accuracy of Topographic Lidar in Data in Coastal Marshes.” *Proceedings of Coastal Zone 09, Boston Massachusetts, July 19-23*. Accessed August 2009 at *www.csc.noaa.gov/cz/*.

Titus, J. 1988. “Sea level Rise and Wetland Loss: an Overview.” In James G. Titus, editor, 1988, *Greenhouse Effect, Sea Level Rise, and Coastal Wetlands.* Washington, D.C. U.S. Environmental Protection Agency. EPA 230-05-86-013. 186 pages.

US Fish and Wildlife Service. 2009. *Technical Procedures for Conducting Status and Trends of the Nation's Wetlands*. 2009. Revised. Accessed October 2009 at *www.fws.gov/wetlands/_documents/gSandT/OtherInformation/TechnicalProceduresConductingStatusTrendsNationsWetlands.pdf.*

Wagner, W., A. Ullrich, T. Melzer, C. Criese, and K. Kraus. 2004. "From Single-Pulse to Full-Waveform Airborne Laser Scanners: Potential and Practical Challenges." *International Archives of Photogrammetry and Remote Sensing*. Volume 35, Part B3. Pages 201 to 206.

Wagner, W., A. Roncat, T. Melzer, A. and Ullrich. 2007. "Waveform Analysis Techniques in Airborne Laser Scanning." *International Archives of Photogrammetry and Remote Sensing*. Volume 36, Part 3. Pages 413 to 418.