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Vertical Accuracy and Use of Topographic LIDAR Data in Coastal Marshes

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ABSTRACT

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Coastal marsh habitat and its associated vegetation are strongly linked to substrate elevation and local drainage patterns. As such, accurate representations of both the vegetation height and the surface elevations are requisite components for systematic analysis and temporal monitoring of the habitat. Topographic Light Detection and Ranging (LIDAR) data can provide high-resolution, high-accuracy elevation measurements of features both aboveground and at the surface. However, because of poor penetration of the laser pulse through the marsh vegetation, bare-earth LIDAR elevations can be markedly less accurate when compared with adjacent upland habitats. Consequently, LIDAR ground-elevation errors (*i.e.,* standard deviation [SD] and bias) can vary significantly from the standard upland land-cover classes quoted in a typical data provider's quality-assurance report. Custom digital elevation model (DEM) generation techniques and point classification processes can be used to improve estimates of ground elevations in coastal marshes. The simplest of these methods is minimum bin gridding, which extracts the lowest elevation value included within a user-specified search window and assigns that value to the appropriate DEM grid cell. More complex point-to-point classification can be accomplished by enforcing stricter slope limits and increasing the level of smoothing. Despite lowering the spatial resolution of the DEM, the application of these techniques significantly improves the vertical accuracy of the LIDAR-derived bare-earth surfaces. By employing the minimum bin technique to the bare-earth classified LIDAR data, the overall bias in the resultant surface was reduced by 12 cm, and the vertical accuracy was improved by 8 cm when compared with the "as-received" data.

ADDITIONAL INDEX WORDS: *LIDAR, marsh, accuracy assessment, digital elevation model, DEM.*

INTRODUCTION

Topographic Light Detection and Ranging (LIDAR) has become a trusted technology for the collection of high-accuracy, high-resolution elevation data, and the widespread availability of vendor-supplied accuracy reports contributes to user confidence (Franklin, 2008). The application of LIDAR data to natural resource management practices, and more specifically, to those associated with the coastal marsh environment, is expected to increase in the near future (Cary, 2009). For example, the use of LIDAR-derived digital elevation models (DEMs) to model marsh evolution and vegetation changes from sea-level rise is becoming a more common practice as the availability of LIDAR data increases and the software continues to evolve (Franklin, 2008). Some of the more common marsh applications of LIDAR data include single-surface (*i.e.,* bathtub) sea-level rise inundation models, the Sea Level Affecting Marshes Model (SLAMM), invasive species mapping, and restoration planning tools (Glick, Clough, and Nunley, 2007; Robinson and Carter, 2006).

The underlying goal of this group of models is to provide guidance on where wetland species will thrive or how they will change in the future, based largely on elevation trends within the landscape. However, when acquired in a coastal marsh environment, research has demonstrated a decreased ability for the laser pulse to penetrate through the vegetative layer to the ground surface (Rosso, Ustin, and Hastings, 2003). Therefore, elevation errors in marshes can be different from the values reported for the adjacent uplands. These differences can potentially result in misuse of the data and/or erroneous conclusions; therefore, a real need exists for quantifying its vertical accuracy. In addition, there is potential to increase the vertical accuracy of the LIDAR data and make it more suitable for marsh-related applications, such as sea-level rise and inundation modeling (Schmid *et al.,* 2009). This study aims to (1) inform users of the limitations of LIDAR data collected in coastal marsh environments, limitations that are often poorly documented in metadata or vendor-supplied accuracy reports; and (2) build on previous research by investigating methods to improve known shortcomings.

Coastal marshes are among the most productive habitats in the world, with low and intertidal portions contributing more

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biomass than the landward and seaward elevation extremes (Cahoon, 1997; Morris *et al.,* 2005). These marshes reside in a specific topographic niche and are largely controlled by the surrounding microtopography; centimeter-level elevation variations can affect nutrient supply and cycling within the marsh (Rosso, Ustin, and Hastings, 2003, 2006). Likewise, the variation in habitat defines its ability to support specific floral and faunal species that ultimately affect the ocean–coastal zone productivity (*e.g.,* fish stocks) (Titus, 1988). Estuarine marshes are also a vital component of green infrastructure, which reduces flood risks, mitigates storm-water effects, improves water quality, and provides hurricane protection (Costanza *et al.,* 2008; Titus, 1988; Weber, 2003). Topography affects the health and function of a marsh and its ability to provide green infrastructure services (Montane and Torres, 2006). Thus, changes in elevation (*e.g.,* low marsh to mudflat) can ultimately affect upland habitats and human health and safety (Titus *et al.,* 2009).

Relative sea-level rise, like the microtopography, is a subtle variable. Past sea-level rise rates are expected to increase; however, the magnitude of change is likely to remain on a scale of millimeters *per* year during the 21st century (Fletcher, 2009; Rahmstorf, 2010). The subsequent response of coastal environments will depend on various geologic, topographic, and morphologic factors. However, marshes may demonstrate dramatic changes because of their sensitivity to subtle elevation variations (Cahoon, 1997; Titus *et al.,* 2009). Kana *et al.* (1998) suggests that physical changes to coastal marshland habitat and its associated vegetation (*e.g.,* low- and high-marsh communities) will be the first indicators of accelerated rates of sea-level rise. Such changes include vertical accretion, marsh habitat translation (*e.g.,* low to high marsh), increased erosion, and loss of vegetation.

Because the relationship between coastal marsh habitat and its characteristic vegetation are largely controlled by substrate elevation and local drainage patterns, accurate high-resolution representations of both vegetation height and ground-surface elevations are requisite components of systematic analysis (Chust *et al.,* 2008; Mason *et al.,* 2005; Morris *et al.,* 2005). Topographic LIDAR data can provide high-resolution, high-accuracy elevation measurements of features both aboveground (*e.g.,* vegetation and buildings) and at the surface (*i.e.,* bare earth) and are available in many coastal regions of the United States (Hopkinson *et al.,* 2004).

LIDAR Collection in Coastal Habitats

LIDAR data have been successfully used to investigate subtle coastal topography and storm changes (Zhang *et al.,* 2005). Unfortunately, within the coastal marsh environment, the ability of LIDAR systems to resolve centimeter-level elevation differences between the vegetation and the bare-earth surface is compromised (Bowen and Waltermire, 2002; Hopkinson *et al.,* 2004). This effect appears to be linked to the physical structure of the marsh vegetation, or more specifically, its erect form, homogeneity, density, and height. The dense and homogeneous nature of erectophile marsh vegetation often results in the collection of LIDAR mass points that closely resemble a flat surface consistent with bare-earth (*i.e.,* ground) elevation and morphology (Gopfert and Heipke, 2006).

Additionally, the resolving threshold of lidar can be at or near the elevation of the marsh returns; the distance between a return from the vegetation and the ground can be less than the "length" of the lidar pulse. For each lidar pulse's reflected energy, there is a level of resolving power that controls the precision of the measurement. The form of the reflected signal, which is dependent on the type of reflecting surface, and the detection algorithms (*i.e.,* what level or shape of the return triggers a "return"), affects the ability of the instrument to define unique returns (Wagner *et al.,* 2004). For example, the reflected energy of a pulse from the first target (*i.e.,* vegetation) can be comingled with the reflected energy of a second target (*i.e.,* ground), with each being unique, depending on the reflecting medium and its angle. The resulting signal can be a complex amalgam of multiple target returns. A variety of detection algorithms are used to separate the individual returns within a signal that is merged, but each algorithm has the potential for loss of returns, noisy returns (*i.e.,* false returns), and erroneous distance calculations (Wagner *et al.,* 2004). As a consequence, individual, reflected impulses separated by less than the pulse length, which can vary from 0.5 to 10 ns apart or approximately 0.1 to 1.5 m, can be difficult to reconcile as "separate" (Hopkinson, 2006; Populus *et al.,* 2001) and may have increased errors.

These aspects are physical and technological limitations of LIDAR systems as they are now being used, and as such, this article does not aim to analyze the error associated with waveform shapes or trigger algorithms, which are commonly proprietary in commercial LIDAR systems (Wagner *et al.,* 2004). Instead, we investigate the error in the mass points (*i.e.,* classified points) that are commonly delivered products in state- and federal-sponsored LIDAR projects. For the purposes of this article, *vertical accuracy* defines the error associated with a sample population of elevation values (*i.e.,* mass points). The error consists of two primary components: (1) bias or offset, and (2) level of precision (*i.e.,* SD).

Most LIDAR data sets are quantitatively evaluated using standardized methods to determine the vertical accuracy of the ground population with respect to different types of land cover. According to Federal Emergency Management Agency (FEMA) specifications, LIDAR data should be tested against ground control points (GCPs) collected in five basic, upland, land-cover categories. These land-cover categories include (1) open terrain, (2) urban or built-up infrastructure, (3) forest, (4) scrub–shrub or low-lying woody vegetation, and (5) weeds, tall grass, and crops (FEMA, 2003). Although the absolute definition of each land-cover class is open to some interpretation, the requirement for collection of GCPs in these five categories is well defined. In most cases, even in coastal-data collections, only a limited number of GCPs are acquired, if any, in marshland cover. Consequently, the vertical-accuracy specifications are not typically cited in LIDAR quality assurance (QA) reports (FEMA, 2003). For marsh-specific studies, the logical outcome is to assume that the vertical accuracy of the weeds, tall grass, and crops category reasonably resembles coastal marsh habitats. Unfortunately, such an assumption may be incorrect, especially if the LIDAR acquisition is timed for minimum vegetation effects (leaf-off conditions).

Previous Applications of LIDAR Data in Marshes

Topographic LIDAR has been employed in marsh-related research throughout the United States, Canada, and Europe. In addition to various modeling and classification exercises, researchers often investigated the vertical accuracy of the LIDAR data, and to the degree possible, attempted to explain errors in the height measurements as some function of the marsh's vegetation properties (*e.g.,* height, density, macrophyte type) and/or processing of the raw LIDAR returns.

Several studies in Europe have used topographic LIDAR data to map coastal habitats and, as a part of the investigation, evaluated their vertical accuracy to determine the appropriateness of the data for use in the intended application. Populus *et al.* (2001) asked the fundamental question of where on the vegetation the LIDAR pulse is reflected. They determined that in dense stands of vegetation, the approximate height of the LIDAR return correlated to one-half of the vegetation height. Concomitantly, they found that the positive LIDAR bias (*i.e.,* LIDAR return from above the ground surface) was directly correlated to vegetation height and density. Gopfert and Heipke (2006) also documented a positive bias that varied as a function of vegetation parameters such as height, density, and species type. The authors reported that height alone did not accurately predict the magnitude of the bias. Although their data were classified to yield bare-earth returns, they concluded that the classification was typically incorrect when actual points hitting the ground were few or absent, or when the vegetation was low enough to make the surrounding bare-earth surface difficult to detect. The LIDAR intensity data did, however, provide useful additional information for making elevation-error assessments.

More recently, Wang *et al.* (2009) used an expanding window technique to improve the chances of capturing true ground returns from a high posting density LIDAR data set (*i.e.,* 8 points *per* square meter) acquired over a heterogeneous marsh system near Venice, Italy. The authors found that only 2–3% of LIDAR returns were actually recorded from the ground surface. A 3.5 × 3.5-m window was chosen as the "optimal" window for this specific data set.

Canadian efforts have focused on determining the vegetation heights of various marsh habitats. With respect to aquatic vegetation in the Alberta province, Hopkinson *et al.* (2004) found that the combination of erectophile vegetation and saturated soil resulted in significant errors in both canopy and ground elevations. The authors concluded that weak returns from saturated soils biased the backscatter (*i.e.,* reflective energy) waveform upward toward the energy reflected from the foliage, whereas the erect vegetation allowed a greater degree of penetration. The result was a poor vegetation-height estimate in aquatic vegetation and a subsequent positive ground-elevation bias of 15 cm. By interpolating the points to a raster, Hopkinson *et al.* (2004) were able to reduce the vertical error of the LIDAR-derived ground surface. They recommend that LIDAR point classification should be selectively performed based on vegetation classification.

Various investigations in the United States have evaluated the vertical accuracy of LIDAR data within estuarine marsh environments located on both the western and eastern sides of the continent. Rosso, Ustin, and Hastings (2003, 2006) evaluated the use of LIDAR to map sedimentation rates as a function of cordgrass (*Spartina* sp.) colonization in the San Francisco Bay. The authors documented a positive bias in the LIDAR-derived ground elevations and inferred that the resultant offset correlated with the middle portion of the vegetation canopy. Rosso, Ustin, and Hastings (2003, 2006) concluded that generic filtering techniques could not differentiate the vegetation and ground returns and suggested the use of such "common" techniques cannot achieve a level of accuracy sufficient to support detailed geomorphology research in estuarine marsh habitats. Research by Sadro, Gastil-Buhl, and Melack (2007) in a California marsh reported a similar result to Wang *et al.* (2009), whereby only a small fraction of the LIDAR points (3%) actually penetrated through the vegetation canopy and hit the ground surface.

A significant amount of LIDAR-related marsh research has been conducted in South Carolina, most notably at the North Inlet–Winyah Bay National Estuarine Research Reserve (NERR). Montane and Torres (2006) reported a positive bias in LIDAR-derived ground elevations of approximately 7 cm. A similar investigation by Morris *et al.* (2005) documented a positive bias of 13 cm, but it should be noted that they employed fewer GCPs in their analysis. Morris *et al.* (2005) concluded that the bias resulted from a combination of (1) poor LIDAR penetration, and (2) errors in the classification and filtering operations.

In summary, the previous research highlights the failure of the laser pulses to penetrate through most marsh vegetation effectively, which prevents the system (the instrument and software) from discerning true ground returns from those returns reflected off the top or inside of the vegetation canopy. This, in turn, results in vertical errors in LIDAR-derived ground elevations that typically manifest as positive biases. These findings generally highlight the problems associated with as-received LIDAR data; LIDAR data acquired over an estuarine marsh have greater limitations than data collected over upland areas (Gopfert and Heipke, 2006; Montane and Torres, 2006).

METHODOLOGY

Ground control was collected *in situ* at five separate estuarine marsh locations to assess the vertical accuracy of a bare-earth–classified LIDAR data set, with respect to variable environmental and habitat conditions. Each site was located in Charleston County, South Carolina, and contained a mixture of macrophytic vegetation types and growth parameters (Figure 1). Two of the sites (Folly Beach and Sullivan's Island) were located in back-barrier marshes, whereas the others had greater riverine influences. The Charleston Navy Base site is a fringing marsh, the Belle Hall location is primarily high or transitional marsh, and the Palmetto Islands County Park site is mixed tidal riverine marsh.

The ground reference data were acquired during a 2-week period between December 2008 and January 2009. By contrast,

Figure 1. Study area and site locations in the greater Charleston, South Carolina area.

the LIDAR data were collected in January 2007. The 2-year separation of measurements is not the ideal case, but the seasonal component was determined to be the most significant aspect controlling vegetation changes in the sampled marshes (Montane and Torres, 2006). Ground reference points were collected at lower tides (*i.e.,* below mean tide level) and were consistent with the tidal constraints on the LIDAR data capture. LIDAR data for all sites were captured below mean tide level; in all cases, the water surface was significantly below the marsh surface. Four of the five sites displayed no signs of rapid change in vegetation vigor or structure. A small portion of the Sullivan's Island site exhibited some discontinuous and/or fragmented vegetation cover and could potentially have had some intra-annual variance in species or vegetative extents. No obviously degraded marshes were sampled.

Short-term, daily to monthly, marsh elevation differences (*i.e.,* shrinking and swelling), driven by tides, rainfall, and evapotranspiration, are possible because of the asynchronous collection. The magnitude of these processes is on the order of millimeters (Paquette *et al.,* 2004), but the ground control and LIDAR data were collected in accordance with Global Positioning System (GPS) techniques that have centimeter-level precision (Zilkoski, D'Onofrio, and Frakes, 2008). Therefore, although these elevational changes are important in yearly marsh accretion (millimeters *per* year) studies, they are beyond the resolution of the techniques used and would be considered "noise" in this study.

Elevation Survey Techniques

The horizontal and vertical positions of the ground reference data were determined using the following methods. Two temporary benchmarks (TBMs) were established in the direct vicinity of the marshes. The TBMs were then surveyed using static GPS techniques to achieve 2- to 5-cm accuracies (Zilkoski, D'Onofrio, and Frakes, 2008). Several sites had existing National Geodetic Survey (NGS) survey markers within close proximity to the targeted sampling areas. In those cases, the NGS benchmarks were used to either validate the accuracy of the static GPS measurements or as survey controls (*i.e.,* TBMs). The NGS's Online Positioning User Service (OPUS) (NGS, 2009) and the Global Navigation Satellites System (GNSS) Solutions software (Version 2.00.3, Thales Navigation, Santa Clara, California) were used to process the GPS data; the solutions were compared to establish confidence in the final coordinates. A total station (GTS-230W, Topcon Positioning Systems, Livermore, California) was set up on one of the TBMs, and the other TBM was used as a backsight. A side-shot direct technique was used to generate positions and elevations at each GCP. The survey rod was fitted with a 9-inch-wide (23 cm), flat base to prevent it from sinking below the marsh surface. The GCPs were primarily collected along transects crossing the marsh surfaces; transects were aligned roughly perpendicular to the upland–marsh boundary. Samples were acquired in areas that approximated the overall nature of the marsh, such that the number of points taken in the various habitats was meant to provide a representative subset of the overall population. Additionally, several points were collected at each site on open, bare-earth terrain to document any local biases in the LIDAR data unrelated to the potentially deleterious vegetation effects. In total, 280 GCPs (223 marsh points; 47 upland points) were collected in and around the five marshes.

Vegetation Parameters

The macrophytic vegetation species (or mixture of species) at each point was defined along with the top of the vegetation canopy height. The dominant species included (1) smooth cordgrass (*Spartina alterniflora*), (2) black needlerush (*Juncus roemerianus*), (3) sea ox-eye (*Borrichia frutescens*), and (4) perennial glasswort (*Salicornia virginica*). Visual estimates of the vegetation density near the surveyed point were also defined. Density was measured as the percentage of ground covered by vegetation, both alive and senescent; 100% density would preclude any view of the ground, and a 25% density would be largely bare ground. This variable was the most subjective of the ground reference data. However, because the same field team collected the data at each of the five sites, the measurement techniques remained consistent.

LIDAR Data

The primary LIDAR data used in this analysis was acquired by Photo Science (Lexington, Kentucky) during leaf-off conditions in January 2007 and February 2007. The data were collected with an ALS50 sensor (Leica Geosystems, Heerbrugg, Switzerland) at a flying height of 1400 m and a total field of view of 33°, which are typical of many county-wide collections, using a pulse rate of 41 kHz (41,000 pulses/s), a scan rate of 75.4 Hz, and sidelap of 28%, which yielded a nominal point spacing of 1.4 m with a targeted vertical root mean square error ($RMSE_Z$) specification of 15 cm. The data provider used TerraScan software (Terrasolid, Leppävaara, Finland) to classify the raw LIDAR data into ground, unclassified, and water points. Although largely proprietary, the general ground classification routine uses local low points within a specified

Table 1. *Vertical accuracy statistics for the as-received 2007 Charleston County, South Carolina, LIDAR data set.*

Land Cover	No. of Points	$RMSE_Z$ (cm)	Mean (cm)	Minimum (cm)	Maximum (cm)	Skew	Standard Deviation (cm)	Vertical Accuracy (cm)
All	75	9.3	−2.0	−25.6	19.1	−0.24	9.2	18.2
Open terrain	26	9.2	−2.8	−19.3	17.2	−0.06	9.0	18.1
Forest	18	10.7	−6.1	−25.6	6.8	−0.59	9.1	21.0
Weeds–Crops	11	7.6	1.1	−10.8	12.8	−0.21	7.8	14.8
Scrub–Shrub	9	10.3	6.3	−8.3	19.1	−0.31	8.6	20.2
Built-Up	11	7.9	2.8	−17.5	5.7	−0.87	7.8	15.5

grid size (*e.g.,* 60 × 60 m) and then iteratively adds points based on angles and distance from the "ground" points. The starting grid size, angles, and distances are set by the user (Soininen, 2010). Thus, unclassified points represent both structures and vegetation; water points are those reflected from the water surface. The data were independently ground-verified in five different land-cover classes and achieved an overall $RMSE_Z$ of 9.3 cm (95% vertical accuracy of 18.2 cm) (NOAA CSC, 2008).

RESULTS

Baseline DEMs were generated using only the bare-earth classified points from the as-received, vendor-supplied LIDAR data. The LIDAR points were interpolated to 2-m grid cells using both Triangulated Irregular Network (TIN) and Inverse Distance Weighted (IDW) techniques. Visual and statistical inspection of the resultant surfaces from the two interpolation techniques yielded negligible differences at the 2-m spatial resolution. The vertical accuracy of the bare-earth surfaces was derived from the marsh-surveyed GCPs. The relationship between the resultant errors was then modeled against the other ground reference variables (*e.g.,* percentage of vegetated ground coverage).

LIDAR Vertical Accuracy: Comparison of Marsh Points to Reported Uplands Categories

The appropriate uses of LIDAR are unique to each data set and are largely dependent on their vertical accuracy in the representative land cover for a given geography. Flood (2004) provides details on reporting the vertical accuracy of LIDAR data. In most cases, the data are tested in the five previously listed land-cover categories: (1) open terrain, (2) urban or built-up infrastructure, (3) forest, (4) scrub–shrub or low-lying woody vegetation, and (5) weeds, tall grass, and crops (FEMA, 2003). The vertical accuracy of the open-terrain category, known as *Fundamental Vertical Accuracy*, is typically used to describe the overall quality of the collection and postprocessing of the data; the other classes help to define the effectiveness of the vegetation and/or structure-removal algorithms to classify the bare-earth surface and are labeled collectively as the *Supplemental Vertical Accuracy*. Lacking GCPs, the general assumption is that the vertical accuracy in marshes is approximated by the weeds–crops or scrub–shrub categories.

Table 1 reports the vertical accuracy of the Charleston County, South Carolina, LIDAR data set with respect to the five standard land-cover categories. A line graph displays the errors for each land-cover category, with the weeds–crops and scrub–shrub classes depicting a small, positive bias (Figure 2). Based on these statistics, one might estimate the vertical accuracy in marshes to be 20 cm (95% confidence; $RMSE_Z$ of 10 cm) with a 5-cm positive bias. When tested separately, however, statistical analysis revealed that the marsh is a unique land-cover category that can have significantly greater errors (SD and bias) than the upland classes (Figure 2). Table 2 reports the vertical accuracy statistics for both the marsh and the consolidated upland land-cover categories; the $RMSE_Z$ of the marsh is more than twice the value of the uplands. More importantly, the mean error is more than 15 cm above the bare-earth surface (a significant, positive bias). It should be noted that the independent, open-terrain check-points collected around the periphery of the marshes displayed nearly the same $RMSE_Z$ (9.0 cm *vs.* 9.3 cm) as the consolidated upland categories.

Considering the vertical accuracy statistics, it is clear that the LIDAR-derived marsh surface includes greater errors with higher positive biases than do the uplands. An unpaired t test was used to assess the mean elevation errors from the upland and marsh groups. The resultant two-tailed p value was less than 0.0001, so by conventional criteria, the difference between the two groups is extremely significant. A similar result (p value of 0.0032) was obtained when the errors from the scrub–shrub and weeds–crops are aggregated to a single group and tested against the marsh errors. Therefore, it is highly likely that the LIDAR-derived, ground-surface elevation errors from the marsh and upland habitats are unique and that substituting upland errors as a proxy for LIDAR performance in marshes is not appropriate.

LIDAR Vertical Accuracy: Site-Specific Analysis

Like most naturally varying environments, each specific marsh habitat exhibits a unique set of biophysical conditions (*e.g.,* salinity, tides, substrates) (Cahoon and Reed, 1995). In light of these differences, the marsh points were divided into site-specific groups to test whether the measured accuracy of one or two marsh locations provided a reasonable estimate of the overall marsh accuracy for the LIDAR-derived ground surface. The $RMSE_Z$ at the various sites ranged from 4.2 to 42.3 cm, a difference of one order of magnitude (Table 3). Sorting the errors by study site highlights some of the similarities and variations between the different marsh habitats (Figure 3). The "flat" portions of the sorted error distributions are consistent with the points sampled in homogeneous stands of *Spartina alterniflora*. By contrast, the "tails" at the ends of the distributions are associated with *Juncus roemerianus* and/or other mixed vegetation samples;

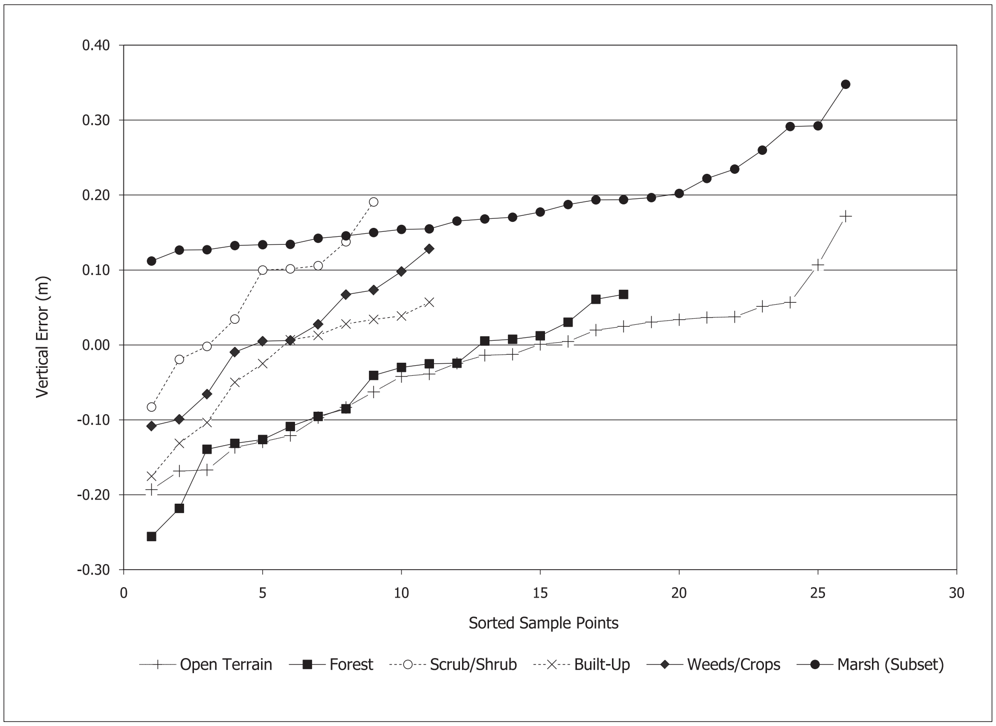


Figure 2. Upland land cover GCP errors with a random selection of marsh GCP errors from the Navy Base, South Carolina site. Points are sorted and plotted by error value from lowest to highest.

these trends were common in each marsh. One notable exception was the mean error (*i.e.,* bias) discrepancy between Folly Beach and the other marsh sites. As a point of comparison, the upland, open-terrain points around Folly Beach also demonstrated an overall negative bias, which was verified by an independent review of the supplemental GCPs. This highlights the site- and flight line–specific aspects of LIDAR data.

The error statistics varied greatly between sample groups and appear to be dependent on species type(s) and its relative abundance. This assumption was confirmed using a one-way analysis of variance (ANOVA); the probability that the resultant errors came from the same distribution is less than 0.0001 (*i.e.,* extremely unlikely). The ANOVA proved that at least one site is different from the other groups; however, the univariate statistics suggest two or more sites could be similar. Examination of box plots reveals that the Palmetto Islands County Park, South Carolina, site contained a significant amount of the overall variability within the total population and had a mean error close to the overall marsh value (15.3 cm *vs.* 18.3 cm) (Figure 4). *Post hoc* t tests were used to compare the Palmetto Islands, South Carolina, vertical errors with the other four locations. As depicted in the box plots, the Palmetto Islands, South Carolina, site was equivalent to both the Navy Base and Sullivan's Island, South Carolina sites, with p values of 0.68 and 0.16, respectively. The Belle Hall and Folly Beach, South Carolina, sites were not similar to each other or to any of the other sites.

LIDAR Vertical Accuracy: Species-Specific Variations

Because the ability to assess the vertical accuracy of LIDAR-derived ground surfaces in marsh habitats requires some understanding of site character, it is important to look at what is different at each site. The simplest answer is the vegetation. As mentioned above, the principal macrophytic species included (1) *Spartina alterniflora,* (2) *Juncus roemerianus,* (3) *Borrichia frutescens,* and (4) *Salicornia virginica*. Each species possesses a relatively unique set of height and density properties. Table 4 reports the vertical accuracy statistics for the ground reference samples as grouped by species type. The $RMSE_Z$ values in the *Spartina alterniflora, Juncus*

Table 2. *Vertical accuracy statistics for the consolidated upland and marsh-land cover samples.*

Land Cover	No. of Points	$RMSE_Z$ (cm)	Mean (cm)	Minimum (cm)	Maximum (cm)	Skew	Standard Deviation (cm)	Vertical Accuracy (cm)
Upland	75	9.3	−2.0	−25.6	19.1	−0.24	9.2	18.2
Marsh	223	23.2	15.3	−13.0	70.4	1.29	17.6	45.7

Table 3. *Vertical accuracy statistics by sample site in South Carolina.*

Land Cover	No. of Points	$RMSE_Z$ (cm)	Mean (cm)	Minimum (cm)	Maximum (cm)	Vertical Accuracy (cm)
Upland	75	9.3	−2.0	−25.6	19.1	18.2
Navy Base	68	21.6	19.4	7.4	65.9	42.3
Folly Beach	56	4.2	−1.7	−8.8	7.7	8.2
Palmetto Island	47	25.7	17.9	−13.0	67.5	50.2
Sullivan's Island	27	14.8	13.2	3.5	28.0	29.0
Belle Hall	25	45.3	38.8	2.2	70.4	88.8

roemerianus, and *Borrichia frutescens* groups are similar to the mean value highlighting the bias of LIDAR data collected in marshes. The *Salicornia virginica* group has a vertical accuracy similar to open terrain (Table 4; Figure 5), which reflects the low density and low height (typically less than 15 cm) of the vegetation. There were a few locations in the *Salicornia virginica* areas with a mixture of *Spartina alterniflora,* which are represented as the filled dots in Figure 5. In fact, if *Juncus roemerianus* is excluded the remaining GCPs sampled in the marsh, the vegetation would have passed FEMA's base LIDAR vertical-accuracy specification (*i.e.,* $RMSE_Z \leq 18.5$ cm). This portends the problem of looking only at RMSE because the bias is, or may be, more important for marsh–coastal applications (Populus *et al.,* 2001).

Interpretation of the standard deviations of the various species also implies that *Juncus roemerianus* is different from the other vegetation, principally *Spartina alterniflora*. This may be a function of its different phenological cycles; whereas the elongated, smooth leaves of *Spartina alterniflora* senesce during the winter, evergreen *Juncus roemerianus* maintains a relatively dense leaf canopy year-round. By contrast, *Borrichia frutescens* is a low-growing, deciduous shrub; however, the $RMSE_Z$ and standard deviation for *Borrichia frutescens* are not significantly different from those of *Spartina alterniflora*. The relative similarities in their elevation-error statistics may be caused by differences in leaf canopy density and/or height. Although *Borrichia frutescens* is shorter (<0.75 m), it is composed of denser, broad leaves that likely result in LIDAR returns off the top of the canopy. *Spartina alterniflora* is typically taller (0.25 to 2.5 m), but the densest portion of the leaf canopy (*i.e.,* where reflection from the LIDAR pulse would be greatest) is significantly closer to the marsh surface. Finally,

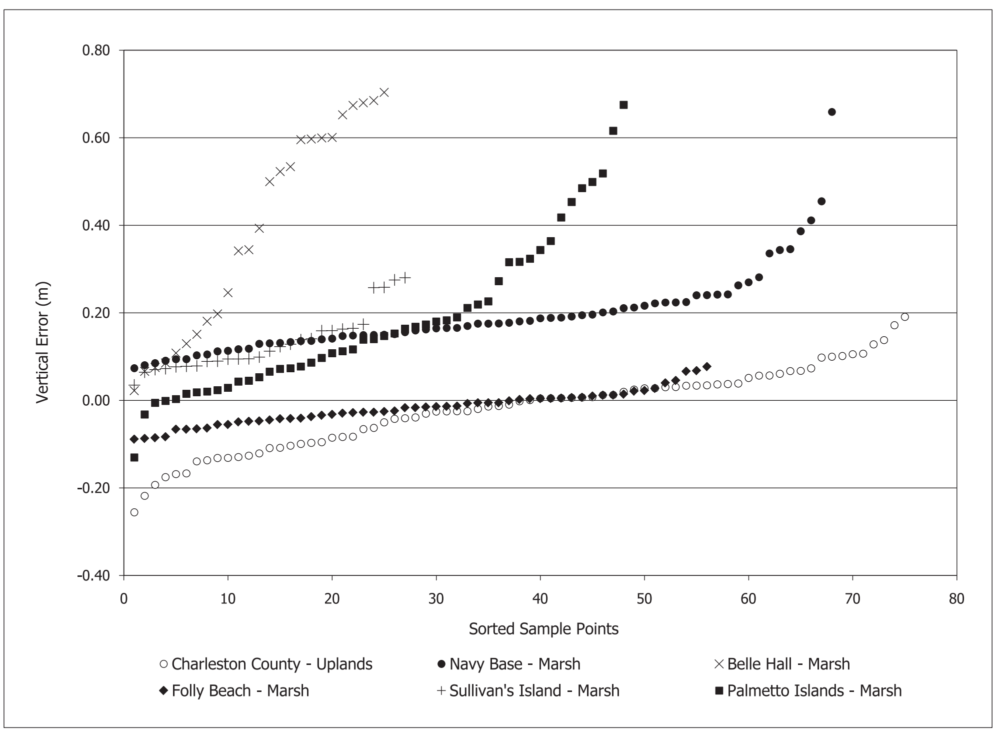


Figure 3. Sorted marsh GCP errors at the five marsh sites and the previously collected upland GCPs. Points are sorted and plotted by error value from lowest to highest.

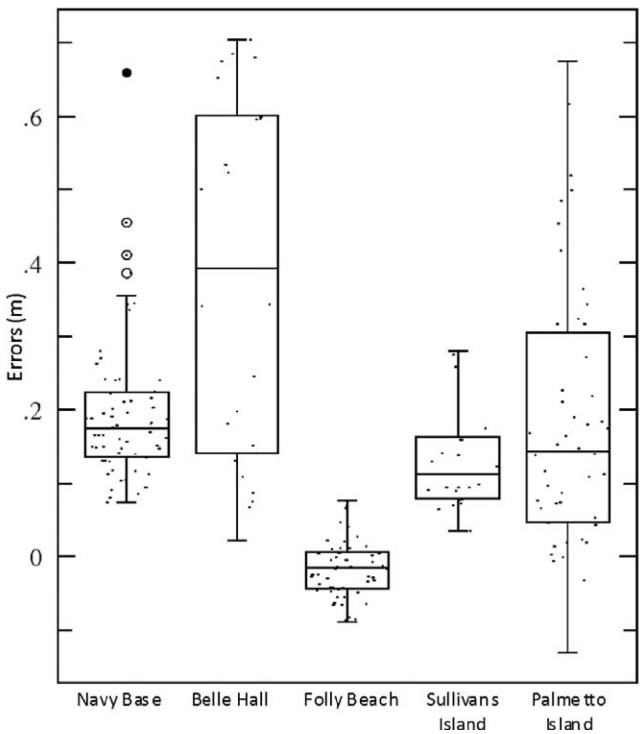


Figure 4. Box plot of the vertical errors from GCPs by marsh site. The box represents the Q1 to Q3 quartiles, the middle line represents the median, and the whiskers extend to the farthest nonoutlier points. Open circles represent outliers, and filled circles represent extreme outliers.

the *Salicornia virginica–Spartina alterniflora* mixture class is a low-growing, perennial herb with erect branches and minute, scaled leaves (Tiner, 1993).

An ANOVA test on the individual species groups returned a p value of 0.0001, which highlights the elevation errors from at least one group as being different from the others. As such, *post hoc* t tests were used to evaluate differences between four species pairs; the four pairs included (1) *Juncus roemerianus* to *Borrichia frutescens*, (2) *Juncus roemerianus* to *Salicornia virginica–Spartina alterniflora*/other, (3) *Juncus roemerianus* to *Spartina alterniflora*, and (4) *Spartina alterniflora* to *Salicornia virginica–Spartina alterniflora*/other. The differences between the pairs were statistically significant for three out of the four tests. *Juncus roemerianus* was different from all the other groups with p values less than 0.0001. *Spartina alterniflora* was different from the *Salicornia virginica–Spartina alterniflora* mixture group (p value of 0.008). Alternatively, error variations between *Spartina alterniflora* and *Borrichia frutescens* were not statistically significant (p value of 0.9987), which again may be related to the interplay of the leaf canopy properties (*e.g.,* height and density) discussed in the previous paragraph. Box plots of the error statistics by species type are shown in Figure 5.

LIDAR Vertical Accuracy: Vegetation Height and Ground Coverage Variations

With respect to *Spartina alterniflora* and *Juncus roemerianus* vegetation species, the elevation-error distributions are significantly different. As noted previously, some of the variance appears to be spatially dependent. For example, variations in the *in situ,* measured *Spartina alterniflora* canopy heights are largely represented by the different sites (Figure 6). The *Spartina alterniflora* heights at Folly Beach, South Carolina, were significantly lower when compared with the other dominant *Spartina alterniflora* marshes (*e.g.,* Navy Base and Sullivan's Island). The height inconsistencies may be associated with the sandier barrier island substrate because the average ground elevations (*i.e.,* flooding regime) were comparable to the other sites. Assuming a hypothetical zero error for a zero vegetation height, the *Spartina alterniflora* "correction factor" for the study sites, excluding Folly Beach, South Carolina, would be approximately $-0.15 \times$ *canopy height* (Populus *et al.,* 2001). The Folly Beach, South Carolina, data are unique and highlight the specific spatial and environmental variability of estuarine marsh vegetation; at Folly Beach, South Carolina, no height correction was needed. The correction factor for *Spartina alterniflora* was, for all study sites, less than the $0.5 \times$ *canopy height* value reported by Populus *et al.* (2001).

Juncus roemerianus displayed a more uniform distribution of height in the sampled marshes (0.5 to 1.5 m). In this case, the least-squares model explained slightly less variation in the relationship between canopy height and error than did the *Spartina alterniflora* model ($R^2 = 0.49$ *vs.* $R^2 = 0.57$). However, the correlation decreased significantly at vegetation heights above 1 m, a result that may again be explained by variations in leaf canopy density. Although the sample size was more limited (*i.e.,* $n = 23$), *Borrichia frutescens* would also appear to benefit from a modeled height-correction factor, whereas 47% of the variance in the elevation error was explained by differences in canopy height.

Density (ground coverage) is another important biophysical variable that contributes to the total elevation error in marsh ground elevations derived from LIDAR data (Gopfert and Heipke, 2006). Unfortunately, modeling the error based on ground coverage alone has limited applicability because of the aforementioned height differences in the various vegetation species. However, if canopy height is multiplied by the density, the resultant independent variable describes 59% of the

Table 4. *Vertical accuracy statistics by macrophytic species type.*

Species	No. of Points	$RMSE_Z$ (cm)	Standard Deviation (cm)	Mean (cm)
Spartina alterniflora	121	15.6	11.4	10.7
Juncus roemerianus	63	36.6	21.6	29.7
Borrichia frutescens	23	14.8	10.4	10.7
Salicornia virginica/mixed	16	11.5	11.9	0.2

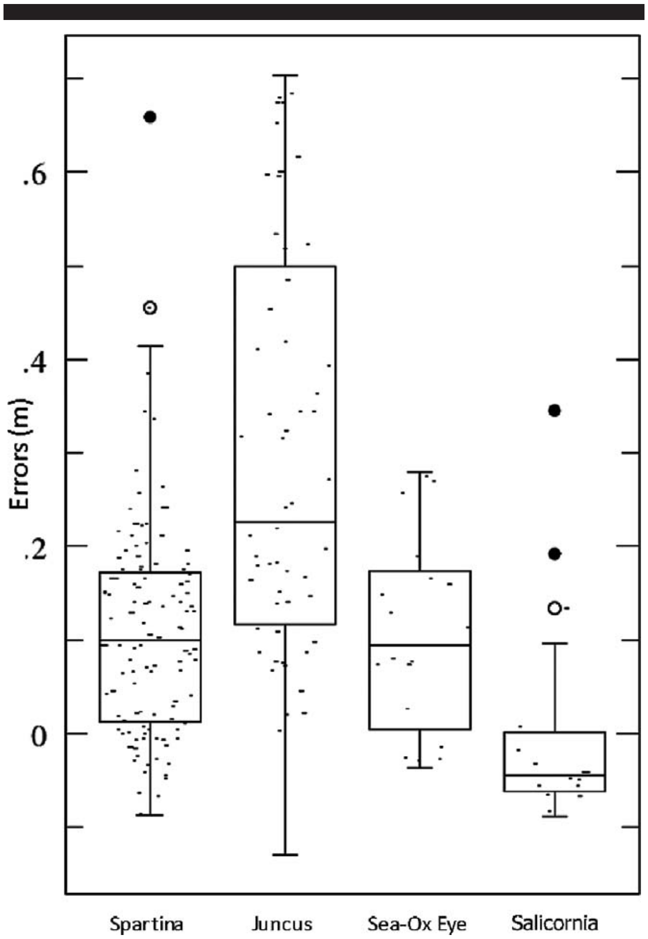


Figure 5. Box plot of species-specific vertical errors for all marsh sites. The box represents the Q1 to Q3 quartiles, the middle line represents the median, and the whiskers extend to the farthest nonoutlier points. Open circles represent outliers, and filled circles represent extreme outliers.

variation in the elevation error (Figure 7). The product of canopy height and density may provide a surrogate measure for vegetation volume. Intuitively, as the vegetation volume increases, the ability of the laser pulse to penetrate through the canopy to the ground decreases, thus resulting in greater elevation errors.

With respect to the sampled vegetation variables, partitioning the data by species had a limited effect on the overall correction factors. Consequently, a single correction factor appears to be applicable for different "*canopy height* $\times$ *density*" values in the two primary marsh species. A linear correction factor of $-0.32 \times$ (*canopy height* $\times$ *density*) fits the taller *Spartina alterniflora* samples well; however, correlation with the elevation error deteriorated at lower "*canopy height* $\times$ *density*" values. The opposite applied to *Juncus roemerianus*, where correlation decreased as vegetation volume increased.

DISCUSSION

The results of this analysis, as well as other investigations by Sadro, Gastil-Buhl, and Melack (2007); Rosso, Ustin, and Hastings (2006); and Populus *et al.* (2001) demonstrate the danger of assuming LIDAR-derived, coastal-marsh ground measurements achieve the same level of vertical accuracy as the upland land-cover categories tested in QA reports. Compounding this problem, the scales of many important biophysical processes, such as tide-controlled vegetation differences, are finer in marshes than in upland and terrestrial habitats (Montane and Torres, 2006; Morris *et al.,* 2005). Thus, the problem of modeling the effects of sea-level rise in marshes, for example, becomes even more problematic.

LIDAR Limitations

The data presented highlight the relationship between vegetation parameters and LIDAR-derived, ground-elevation errors. To a large degree, the elevation errors can be explained by variations in vegetation type (species), density, and canopy height; however, site-specific variability is also a factor. As a result, the ability to vary processing based on vegetation or habitat parameters could improve data accuracy. Full waveform interpolation is not currently employed in the state-of-the-practice, commercial, terrestrial, LIDAR acquisition and processing; full waveform digitization would provide some ability to discern different vegetation and apply specific detection methods (Wagner *et al.,* 2004). The software and technical capacity required to process full waveform LIDAR data is coming but, at present date, is not a viable practice (Franklin, 2008).

At present, specifications on LIDAR collections, such as flight height, pulse rate, sensor type, and field of view, can be adjusted to increase point density and the likelihood of vegetation penetration (Hopkinson, 2006). These modifications can also increase collection costs, especially if the data are being collected on a county-wide scale, and in many cases, the data being used have already been collected. Varying classification routines, which are typically proprietary, is another avenue, but in regional/county collections, the use of varying routines can create unwanted inconsistencies in DEM character (*e.g.,* changes in the native resolution) across the project area.

The essence of the problem is illustrated in Figure 8. The LIDAR returns in this *Spartina alterniflora*–dominated marsh are consistently recorded above the ground surface. Although they are below the middle of the vegetation canopy, they do not represent the bare-earth elevations. It is interesting to note that, in the marshes studied, very few points were left unclassified (not ground), and nearly all were single returns (*i.e.,* 1 of 1), even though the marsh vegetation was consistently greater than 1 m in height. The fact that nearly all points were classified as ground (albeit incorrectly) effectively removes the dependence on classification routine as a factor in the present analysis and increases the potential for further automated processing as a solution. However, the lack of true returns from the ground surface, as well as their relative uniformity represents significant obstacles for most LIDAR-classification algorithms (Gopfert and Heipke, 2006). The paucity of "real" ground returns is likely a product of the LIDAR instrument's resolution and the ability of the software to recognize discrete returns in the reflected waveform (Wagner *et al.,* 2004, 2007).

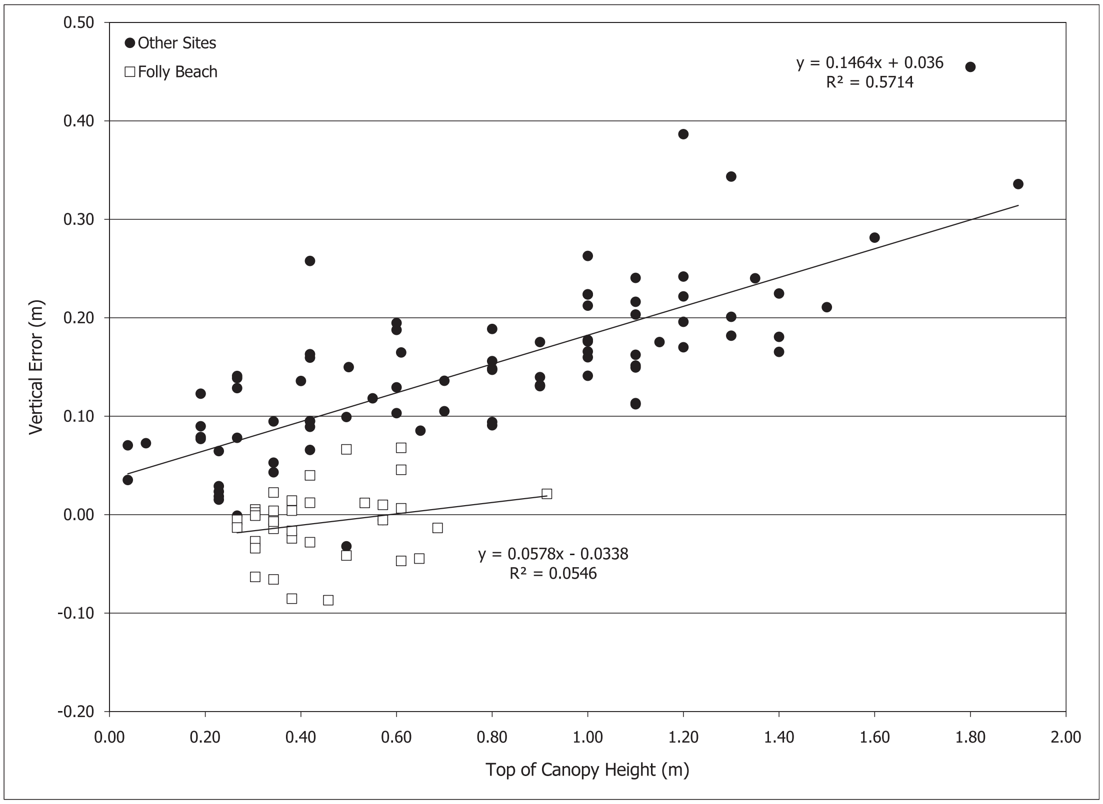


Figure 6. Scatter plot of *Spartina alterniflora* canopy heights against elevation errors for each GCP; one outlier removed.

The diffuse returns from erectophile marsh vegetation, coupled with saturated soils, can create an ambiguous signal that results in a false ground return (*i.e.,* a return from above the ground surface) (Figure 9). As mentioned, advanced, full-waveform, LIDAR systems, such as the Experimental Advanced Airborne Research LIDAR or commercially available systems from Riegl Laser Measurement Systems, GmbH (Horn, Austria) and Optech Inc. (Vaughan, Canada), provide an alternate avenue for defining the location of points. Various algorithms designed to exploit the full-waveform signal could be used in marsh or coastal areas to better establish return elevations (Fowler *et al.,* 2007). In addition, smaller-footprint systems may have the ability to better exploit open spaces in the marsh vegetation.

In the near term, LIDAR data will continue to have vegetation-generated errors in coastal marshes. Errors can be minimized by collecting data during seasonal windows when plant canopies are at their lowest levels. That being said, the LIDAR data employed in this investigation were acquired during lower tides and leaf-off conditions yet still exhibited significant vertical errors. To address the vertical errors associated with LIDAR points in marshes, several techniques were evaluated to produce more accurate bare-earth DEMs. These techniques are intended to improve shortcomings in the as-received data, as opposed to solving the problem at an operational level.

Techniques for Correcting LIDAR-Generated Products in Marshes

Various techniques are available for end users to generate or interpolate DEMs from as-received LIDAR data. Although this analysis focuses specifically on the bare-earth surface, similar methods could be employed to develop a first return or vegetation canopy-height digital surface model. The entire collection of LIDAR points can be used, or the data can be modified, selected, or segregated to improve the resultant surface. It would be incorrect to assume that the as-received LIDAR data set is the optimal one for all applications (Franklin, 2008; Maune *et al.,* 2007).

From an end user's perspective, raster-based DEMs are typically the elevation product of choice. Spatially explicit models and contours commonly use or are derived from bare-earth DEMs. However, not all DEMs are generated the same way nor are their creations beholden to any one specific standard (Maune *et al.,* 2007). Development of DEMs is often an iterative process that requires knowledge of the data (*e.g.,* bias) and its intended use. Simple spatial-interpolation techniques, such as IDW and natural neighbors, have traditionally been the preferred method; however. more-advanced techniques (*e.g.,* kriging, splines, decimation, and breaklines) are appropriate in situations in which the data do not meet the need (*e.g.,* not bare-earth filtered), require

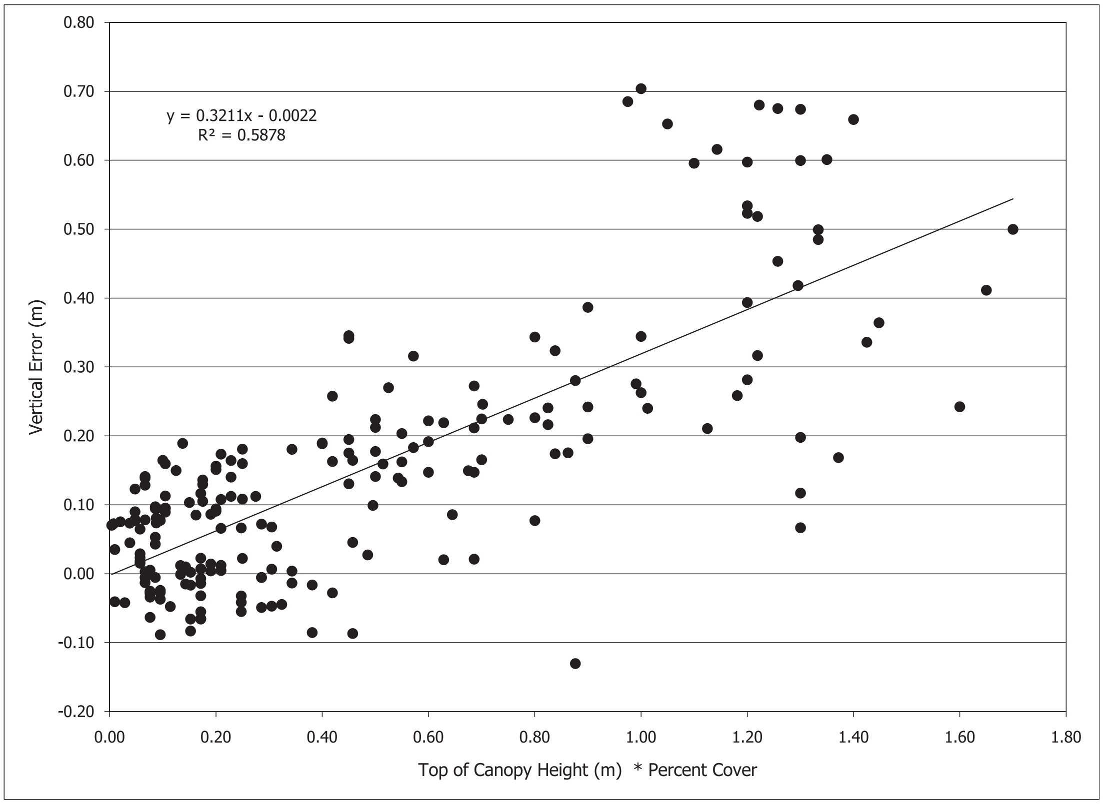


Figure 7. Scatter plot of density multiplied by canopy height against elevation error for all vegetation types.

additional information (*e.g.,* hydro-correction), or have specific collection properties (*e.g.,* low point density) that are not well suited for use with the more traditional methods (Maune *et al.,* 2007).

LIDAR point data can also be processed before DEM generation in a step known as filtering, classification, or postprocessing (Fowler *et al.,* 2007). As with raster-based DEM creation, users are afforded a large suite of software tools to manipulate the base LIDAR data. In short, the as-received data provided are, or can be, open for greater refinement; it should not be assumed that the maximum quality has been achieved from a delivered data set, especially in difficult geographies such as marshes.

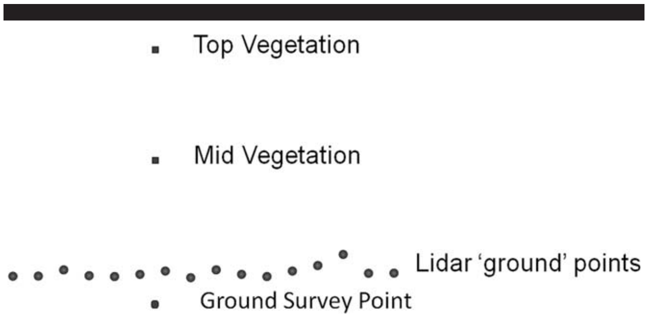


Figure 8. Scaled schematic of the LIDAR profile generated through *Spartina alterniflora*–dominated marsh at one GCP vertical-profile location. The control location consists of three points: a surveyed ground point, a measured middle vegetation point, and a measured top-of-vegetation point. This is common of most profiles examined, with the LIDAR "ground points" elevated slightly above the independently measured ground.

The results reported in the "Results" section represent the baseline data (*i.e.,* no user modifications were made to the as-received data set) and will be used to quantitatively assess the differences between the "user-modified" and "as-delivered" DEMs. The collected marsh GCPs are used to calculate statistics of the user-modified DEMs in the same manner as the as-delivered DEMs. Two techniques to create the user-modified DEMs were explored: (1) custom gridding, and (2) custom filtering.

Custom Gridding

As discussed, there are many ways to generate a DEM from point data, with choice of interpolation and gridding routines and varying the resolution being the most common differences (Maune *et al.,* 2007). Using these techniques, we attempted to derive a DEM that more accurately represented the bare-earth surface in the marsh. With the exception of tidal creeks, topographic variations in marshes are generally limited over small spatial extents. This affords users the option to decrease

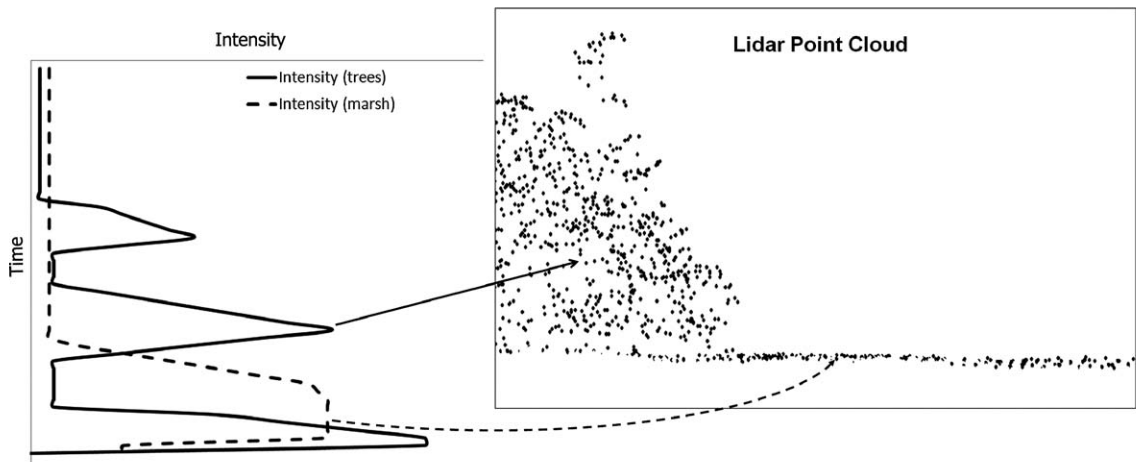


Figure 9. Hypothetical waveform (intensity trace) from marsh and upland laser pulses and actual LIDAR profile across the upland–marsh boundary. The diffuse character of marsh waveforms, as compared with upland areas, can bias data such that marsh points are higher than the upland land points (under trees).

(*i.e.,* coarsen) the spatial resolution of the DEM while only sacrificing a limited amount of the elevation detail. For example, in flat areas, a 4- to 6-m DEM can, in most cases, provide the same level of information as a 1- to 2-m DEM (Maune *et al.,* 2007). Another consideration is the spatial extent of the DEM beyond the marsh boundary and the relative importance of upland feature definition. Where discontinuous marsh is present or upland areas dominate, the use of point classification may provide a better option to custom gridding.

Earlier investigations documented only minor improvements using different deterministic (*e.g.,* IDW) and geostatistical (*e.g.,* kriging) interpolation models with high postspacing LIDAR data (*i.e.,* >0.5 points/m) (Rosso, Ustin, and Hastings, 2003, 2006). As a result, this study used a simple "bin-type" gridding technique. Binning methods are fundamentally different from interpolation in that points are removed from the data set. This approach is consistent with the overall goal of filtering, considering that the as-received LIDAR data included many nonground points incorrectly classified as ground. The fundamental question then becomes whether the resolution is more important than accuracy. If accuracy is the objective, the expense of removing small-scale topographic features can be justified by the removal of erroneous points (*i.e.,* those above the bare earth) to better model the overall ground surface.

Minimum bin-gridding from LIDAR data has been shown to reduce vertical errors in vegetated cover, but in open areas (*e.g.,* mud flats), it can produce elevations below the true ground surface (*i.e.,* negative bias) (Rosso, Ustin, and Hastings, 2003). The method selects the lowest elevation point in a predefined lattice (a structured grid at the user-specified spatial resolution) to represent the elevation in each grid cell of the output raster. In a case in which the resolution of the lattice is approximately equal to the nominal postspacing of the LIDAR data, the output value would be defined by a single point; as the lattice resolution coarsens, the range of the input elevations will likely increase. As such, spatial resolution is the primary parameter to control the output surface, and changing the resolution will produce DEMs with different elevation characteristics (Figure 10). To quantify the differences, the marsh GCPs were tested against minimum bin DEMs generated at spatial resolutions ranging from 2 to 10 m. The resultant error statistics were compared with the as-received (*i.e.,* IDW interpolated) data to ascertain the characteristics of the custom DEMs, as well as to determine the spatial resolution that provided the most improvement.

Error statistics for the minimum bin and IDW-interpolated grids at varying spatial resolutions for the Charleston Navy Base, South Carolina, site are shown in Figure 11. With the exception of the 10-m grid, the minimum bin method resulted in lower $RMSE_Z$ and bias values at each tested spatial resolution. Additionally, all of the resampled grids (*i.e.,* both the minimum bin and the IDWs > 2 m) exhibited lower $RMSE_Z$ values than the standard 2-m IDW-interpolated grid. The best results in the *Spartina alterniflora*–dominated Navy Base site were achieved using a 4-m minimum bin grid ($RMSE_Z$ = 0.17 m, SD = 0.13 m, bias = 0.12 m). By contrast, the Belle Hall, South Carolina, site, composed almost exclusively of *Juncus roemerianus*, required a larger minimum search radius to achieve a comparable improvement in the $RMSE_Z$; optimal results were realized with a 10-m minimum bin ($RMSE_Z$ = 0.12 m, SD = 0.1 m, bias = 0.07 m) (Figure 12). Because the Belle Hall, South Carolina, site is predominantly high or transitional marsh with few tidal creeks or other abrupt changes in elevation, a coarser spatial-resolution DEM appears acceptable. With respect to selecting the optimal spatial resolution, the ideal solution would define the bin size as a function of the specific vegetation parameters (*e.g.,* species, ground coverage, and canopy heights) in the marsh of interest. However, in most cases, information about the vegetation is not collected.

To evaluate the overall suitability of the minimum bin method for both marsh and upland land-cover categories, a 5-m minimum bin surface was generated over the complete extent

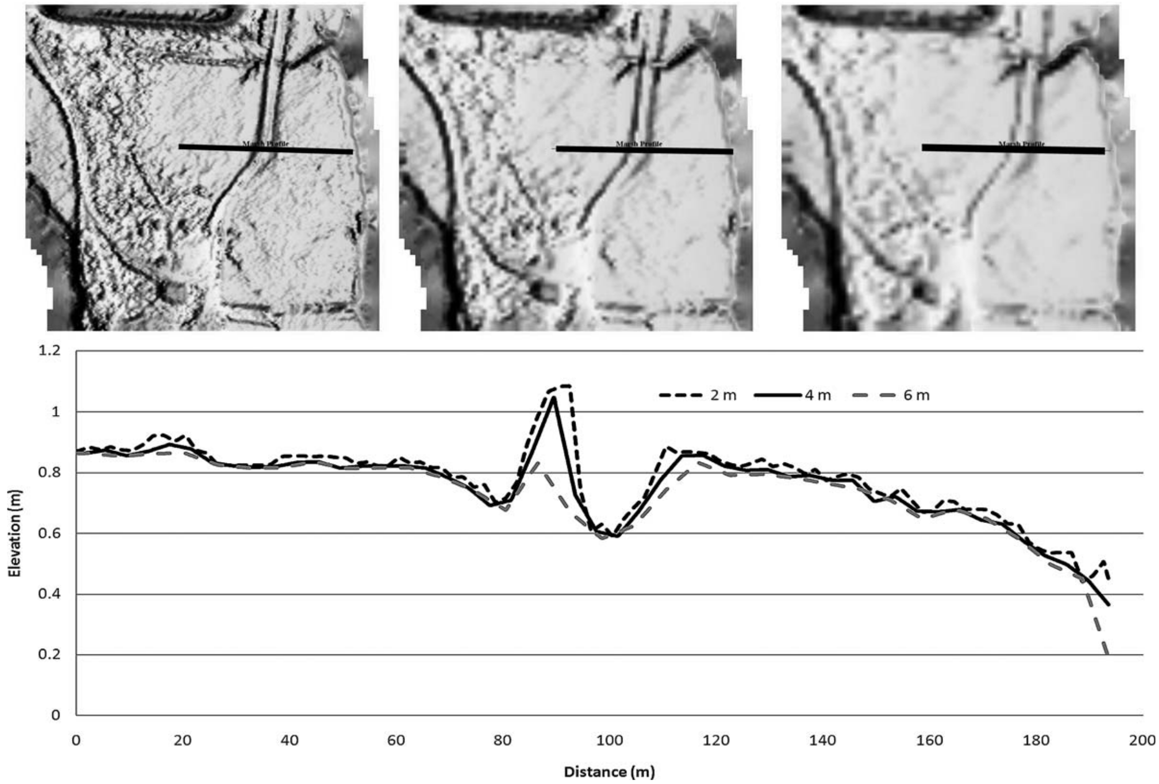


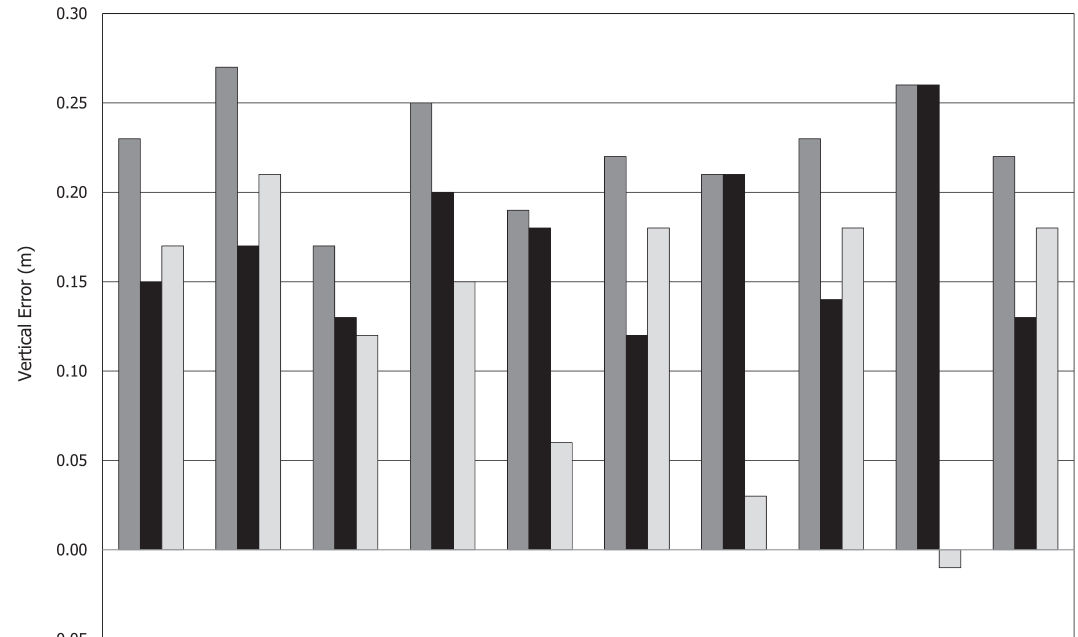
Figure 10. DEMs generated with the minimum-bin technique and grid cell sizes varying from 2 to 6 m (from left to right) with their associated elevation profiles.

of the Charleston County, South Carolina, LIDAR data. The resultant surface was then compared with the baseline 2-m DEM interpolated from a TIN. The 5-m resolution represented a compromise based upon various biophysical and data-specific factors, including (1) the heterogeneity within and between marshes (*e.g.,* vegetation species and substrate), (2) the variations in marsh and upland habitats, (3) the areal extent, and (4) the postspacing of the LIDAR data. The vertical accuracy was then tested using both the marsh GCPs collected for this analysis and the 75 previously collected upland GCPs initially used to QA the LIDAR data (NOAA CSC, 2008).

As hypothesized, the vertical errors in the 5-m Charleston County, South Carolina, minimum-bin DEM were less biased and had a lower $RMSE_Z$ in the marsh areas than did the 2-m TIN-derived DEM (Table 5). However, the minimum bin technique may undersample areas with steeper slopes or near tidal streams (*i.e.,* results in negatively biased elevations), as evidenced by a 12.1-cm decrease in the mean vertical error. In the upland areas, the resultant $RMSE_Z$ and bias statistics were poorer for the minimum-bin surface than they were for the TIN-derived DEM. Although the upland $RMSE_Z$ of 18.2 cm would meet FEMA's base vertical-accuracy specification (*i.e.,* $RMSE_Z \leq 18.5$ cm), the resultant elevation values were negatively biased by 11.3 cm. Consequently, an 11.3 cm adjustment (*i.e.,* increase) of the DEM's values in the upland areas (*e.g.,* >1 m North American Vertical Datum of 1988) would both remove the negative bias and decrease the upland $RMSE_Z$ to approximately 14 cm. Such a correction would result in a fairly accurate DEM, and more importantly, a nonbiased, bare-earth surface for both the upland and marsh areas.

Custom Filtering

LIDAR point classification represents a more complex and resource-intensive avenue to manage the challenges associated with the paucity of true ground returns in a marsh environment. Classification, however, has the advantage of being more discriminating than the previously discussed minimum-binning technique. There are many different types of classification or filtering algorithms (*e.g.,* refer to Zhang and Cui, 2007), but given their inherent complexity and often proprietary nature, specifics about the processes are seldom explicit. In the following examples, the automated bare-earth extraction algorithm in LASEdit (Cloud Peak Software LLC, Version 1.15.1, 2007, Sheridan, Wyoming) was employed with an emphasis placed on high-frequency noise reduction (*i.e.,* generalization of the ground surface) and flat-terrain bias. This translated broadly to a combination of larger search windows and finer slope thresholds. Defining the exact parameters or algorithm is not the purpose of this work but rather assessing the applicability of higher sensitivity, as well as where improvements can be made and where the process has deleterious effects on usability.



	2m Min Bin	2m IDW	4m Min Bin	4m IDW	6m Min Bin	6m IDW	8m Min Bin	8m IDW	10m Min Bin	10m IDW
RMSEZ	0.23	0.27	0.17	0.25	0.19	0.22	0.21	0.23	0.26	0.22
Std Dev	0.15	0.17	0.13	0.20	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

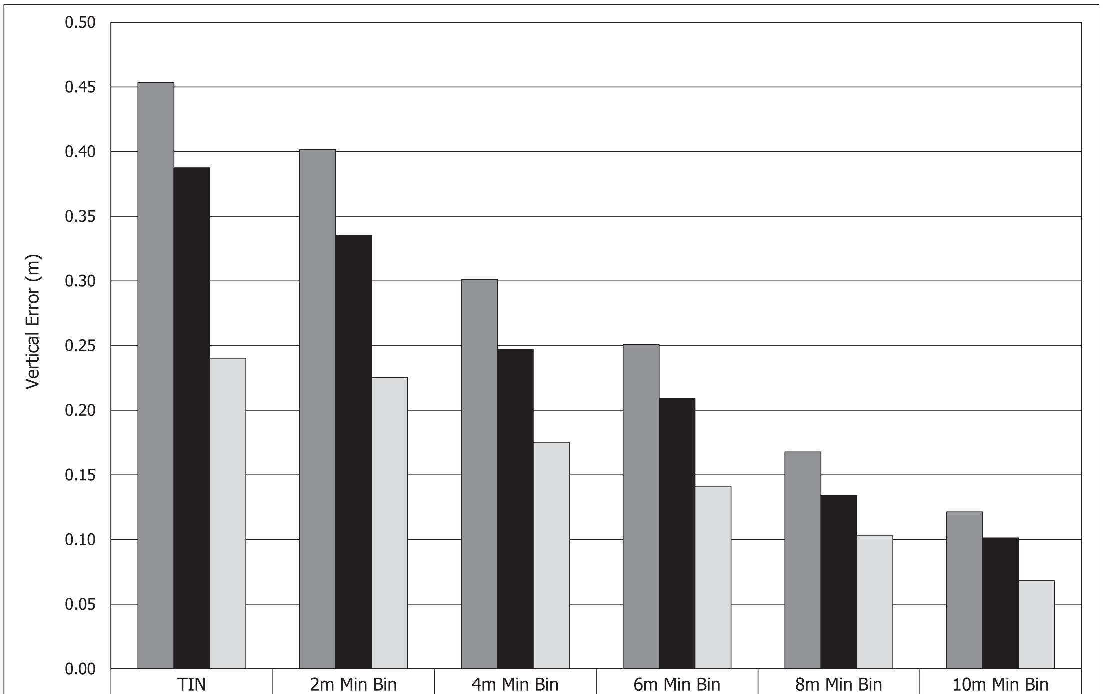
Figure 11. Error statistics of marsh GCPs when varying DEM-generation parameters at Navy Base site, South Carolina.

Similar to the binning methods, there is a loss of detail when increasing the sensitivity of the classification algorithm; more points are removed, thus resulting in lower point density. The principal advantage of filtering is the potential to discern critical elevation points and maintain sufficient point density to represent real topographic features (*e.g.,* tidal channels). For example, the Palmetto Islands County Park study site was a subset from the as-received Charleston County, South Carolina, LIDAR data and was iteratively filtered using incrementally flatter terrain biases and increased generalization to tune the classification. Figure 13 displays three different iterations of point-classification sensitivity, ranging from the as-received data (*i.e.,* no additional filtering) to moderate and ultimately high levels of filtering (filtering increases from left to right). The Palmetto Islands, South Carolina, site consisted of a mixture of *Spartina alterniflora, Juncus roemerianus,* and *Salicornia virginica*. Field samples were collected in the marsh located in the central portion of the images. Ground-classified points are shown in purple, unclassified points in tan/brown (*e.g.,* trees and other high vegetation), and low vegetation in green. As the sensitivity of the filtering increased, greater numbers of potentially erroneous ground-classified points were reclassified to low vegetation (*i.e.,* marsh vegetation). The pattern that emerges highlights the taller *Spartina alterniflora* adjacent to the tidal creeks and the *Juncus roemerianus* that dominates the interior, higher marsh.

To quantify the postclassification effects on the vertical accuracy of the LIDAR data, TIN-derived elevations from the remaining ground-classified points were compared against the Palmetto Island County Park GCPs. The resultant statistics showed significant vertical-accuracy improvements in both the complete sample set (*i.e.,* 47 samples) and the *Juncus roemerianus* points (*i.e.,* 36 samples) (Table 6). By contrast, the *Spartina alterniflora* points (*i.e.,* 10 samples) demonstrated only minor variations in the error statistics. However, the as-received data in the areas dominated by *Spartina alterniflora* were quite good. It should also be noted that positive biases, albeit less, remained in the filtered data sets.

CONCLUSION

Based upon the results of this investigation, the following conclusions were drawn: (1) LIDAR data errors from coastal marsh habitats are not the same as those from upland habitats, which are commonly quoted in accuracy reports; (2) bare-earth LIDAR points in marsh habitats can have a significant positive (*i.e.,* aboveground) bias; (3) different vegetative types and densities affect the error of the LIDAR data; (4) vertical accuracy of as-received topographic LIDAR data acquired within the coastal marsh environment can be improved using custom DEM-generation techniques; and (5) users should not assume that the as-received LIDAR data set represents the "best" or "most appropriate" surface for their intended use or application.



	TIN	2m Min Bin	4m Min Bin	6m Min Bin	8m Min Bin	10m Min Bin
RMSEZ	0.45	0.40	0.30	0.25	0.17	0.12
Bias	0.39	0.34	0.25	0.21	0.13	0.10
Std Dev	0.24	0.23	0.18	0.14	0.10	0.07

Figure 12. Error statistics of marsh GCPs when varying DEM-generation parameters at Belle Hall site, South Carolina.

Two techniques (*i.e.,* minimum bin gridding and point classification) for generating an improved DEM in coastal marshes were reviewed; however, by no means, do they represent the full range of possible solutions. Rather, they are examples of relatively simple methods that could be implemented by either end users or data producers to enhance data quality. The specific algorithm, bin size, bin type (*e.g.,* minimum, maximum, or average), and level of effort required to realize meaningful improvements in the as-received data is dependent on a number of biophysical and data-specific factors. Such factors may include marsh vegetation variations (*e.g.,* species type, percentage of ground coverage, canopy height, *etc.*), the areal extent and topographic complexity of the marsh, the nominal posting density of the LIDAR data, and ultimately, the level of vertical accuracy that is required for the application.

When quantitative QA is warranted or required, the vertical accuracy of as-received bare-earth marsh elevations should be tested against GCPs collected inside the marsh, as intuitively similar land-cover categories (*e.g.,* weeds–crops and scrub–shrub) have proven to be unreliable predictors of LIDAR performance. Additionally, coastal marshes are, by definition, composite environments that often exhibit heterogeneous mixtures of vegetation species caused by dynamic hydrologic and substrate conditions. As such, it is advisable to systematically sample at several targeted locations that include high species diversity. This is somewhat different from the random sampling strategy typically applied to accuracy assessments of upland land-cover categories.

Table 5. *Comparison of the vertical accuracy statistics for DEMs derived with the minimum-bin and TIN methods.*

Land Cover	DEM	$RMSE_Z$ (cm)	Mean (cm)	Standard Deviation (cm)
Upland	TIN	8.8	0.6	8.8
	5-m BIN	18.2	−11.3	14.3
Marsh	TIN	23.3	15.3	17.6
	5-m BIN	15.6	3.2	15.3

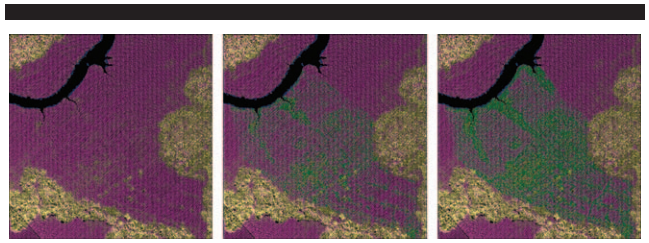


Figure 13. Increasing filtering levels in a portion of the marsh (central area of the figures) from as-delivered (low magnitude) to highly filtered (left to right). The lighter-colored (green) points in the marsh have been classified as "low vegetation" and removed from the bare-earth (purple) data set; the yellow points were initially removed.

Table 6. *Vertical accuracy statistics for Palmetto Islands County Park, South Carolina, marsh site using different levels of point classification sensitivity.*

Species	Classification Sensitivity	$RMSE_Z$ (cm)	Mean (cm)	Standard Deviation (cm)
All Samples	As-received	25.7	17.9	18.1
	Moderate	21.4	14.8	15.6
	High	16.2	11.3	11.7
Juncus roemerianus	As-received	29.2	23.1	18.0
	Moderate	24.4	18.6	15.9
	High	18.4	14.1	11.9
Spartina alterniflora	As-received	3.5	2.1	3.0
	Moderate	3.2	1.8	2.7
	High	3.0	1.5	2.7

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