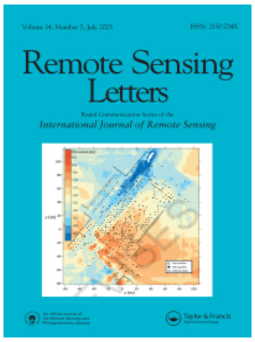

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Assessing the vertical accuracy of digital elevation models by quality level and land cover

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ABSTRACT

The vertical accuracy of elevation data in coastal environments is critical because small variations in elevation can affect an area's exposure to waves, tides, and storm-related flooding. Elevation data contractors typically quantify the vertical accuracy of lidar-derived digital elevation models (DEMs) on a per-project basis to gauge whether the datasets meet quality and accuracy standards. Here, we collated over 5200 contractor elevation checkpoints along the Atlantic and Gulf of Mexico coasts of the United States that were collected for project-level analyses produced for assessing DEMs acquired for the U.S. Geological Survey's Three-Dimensional Elevation Program. We used land cover data to quantify non-vegetated vertical accuracy and vegetated vertical accuracy statistics (overall and by point spacing bins) and assessed elevation error by land cover class. We found the non-vegetated vertical accuracy had an overall root mean square error of 6.9 cm and vegetated areas had a 95th percentile vertical error of 22.3 cm. Point spacing was generally positively correlated to elevation accuracy, but sample size limited the ability to interpret results from accuracy by land cover, particularly in wetlands. Based on the specific questions a researcher may be asking, use of literature or fieldwork could assist with enhancing error statistics in underrepresented classes.

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1. Introduction

Elevation data are used across many science fields for understanding an area's ecological, geomorphological, and hydrological attributes. In coastal environments, elevation is used for modelling exposure to physical stressors such as coastal inundation from waves, storm surge, and sea-level rise (Gesch 2018), mapping habitat coverage (Enwright et al. 2023), and assessing morphological change (Wernette, Lehner, and Houser 2020). The accuracy of elevation data is critical in

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coastal environments where small elevation changes may lead to increased hydrological impacts from salt spray and exposure to oceanic water from tides, waves, and extreme storms. Vertical errors in digital elevation models (DEMs) produced from conventional manned aerial lidar data acquisitions can affect the accuracy of elevation-based inundation modelling, including forecasting of wetland persistence under sea-level rise (Medeiros et al. 2015) and coastal inundation modelling efforts that rely on elevation data (Barnard et al. 2014). Consequently, elevation accuracy information can be helpful for researchers working with remotely sensed elevation data, especially in dynamic and low-lying coastal settings.

Multiple factors can affect the capture and accuracy of lidar-derived DEMs, including vegetation type and characteristics, slope, and hydrology (Paul, Buytaert, and Sah 2020; Su and Bork 2006). The spacing between lidar pulses can also influence the accuracy of the resulting DEM, as higher point density may allow for lidar to penetrate deeper between vegetation to the ground (Salach et al. 2018). Lidar contractors use in situ elevation data collection via surveying (hereafter called 'checkpoints') to assess the accuracy of lidar acquisitions and products, such as DEMs. A newly revised edition of the American Society for Photogrammetry and Remote Sensing (ASPRS) Positional Accuracy Standards for Digital Geospatial Data calls for at least 30 points collected via ground-truth Global Navigation Satellite System (GNSS) observations in non-vegetated and vegetated areas for ensuring that the lidar and its resulting DEM meet quality standards (ASPRS 2023).

Several studies have assessed accuracy beyond acquisition-level extents. Gesch, Oimoen, and Evans (2014) used an inventory of around 25,000 National Geodetic Survey geodetic control points and a database of Online Positioning User Service (OPUS) points to assess the accuracy of the U.S. Geological Survey's (USGS) 1/3rd arc-second National Elevation Dataset across a variety of land cover classes. Stoker and Miller (2022) built upon this work by using similar sources, but also aggregated vertical accuracy checkpoints provided by contractors for each individual lidar acquisition to assess the accuracy and feasibility of a seamless version of USGS Three-Dimensional Elevation Program (3DEP) DEMs across the conterminous United States.

Due to the importance of elevation in coastal environments and the abundance of coastal wetlands, which commonly have high elevation error (Enwright et al. 2023), updated information on accuracy using contractor checkpoints in coastal environments could provide a better understanding of elevation accuracy in coastal areas. Here, our research objectives were to use vertical accuracy checkpoints provided by contractors for each lidar acquisition to assess: 1) common summary statistics for lidar elevation accuracy (i.e., non-vegetated vertical accuracy [NVA] and vegetated vertical accuracy [VVA]); 2) elevation accuracy by lidar point spacing levels; and 3) elevation accuracy by land cover type. One challenge is that lidar checkpoints that have been historically collected for 3DEP were not standardized regarding file formats and summary statistics. This study also presents a process and recommendations for future work related to collating and extracting elevation accuracy data from contractor-provided elevation checkpoints.

2. Materials and methods

2.1. Study area and data

The study area encompasses the Atlantic and Gulf of Mexico coasts of the United States. We focused our study on the coastal areas by using U.S. counties that intersect the Category 5 Maximum of the Maximum Storm Surge Inundation Extent (NOAA 2022) to determine the inland extent of the coastal region. This study area (Figure 1) is comprised of 297 counties within portions of 20 states and has a total of 575,819 km^2.

The elevation data used in this project were from the USGS 3DEP, which collates and publishes national elevation data (USGS 2023). The 3DEP makes elevation data publicly available through USGS web maps, Amazon web services, including direct links on the 'RockyWeb' USGS server (accessible at https://rockyweb.usgs.gov/vdelivery/Datasets/Staged/Elevation). Spatial metadata for the USGS 3DEP is contained

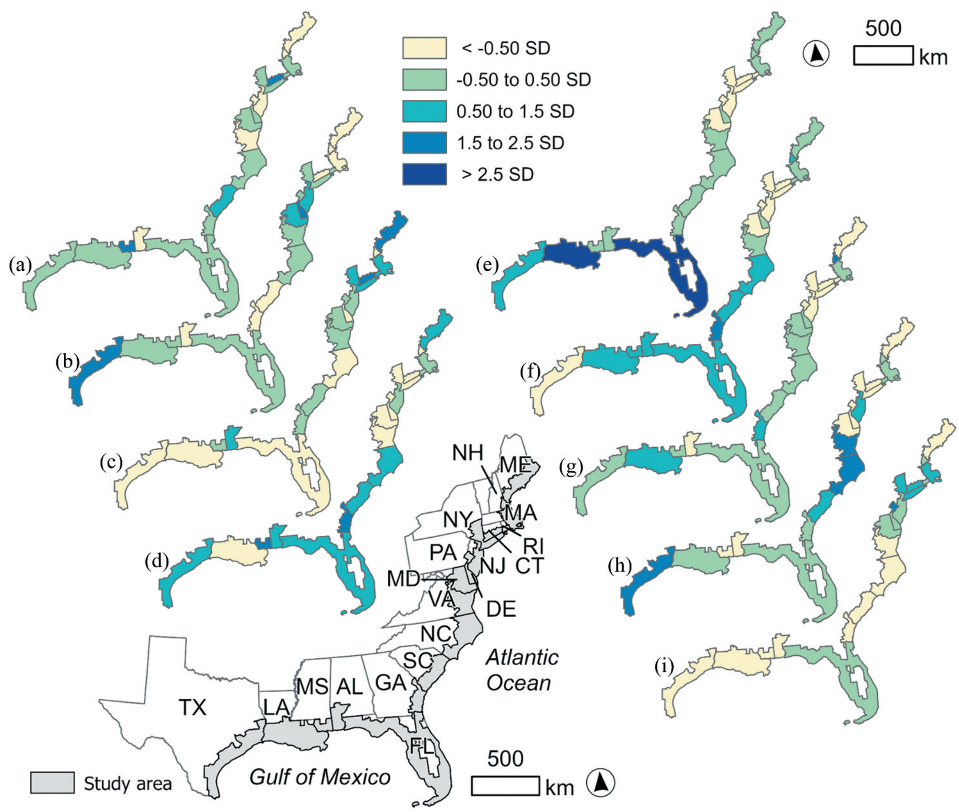

Figure 1. State-level distribution of checkpoints and land cover types used to assess the vertical accuracy of digital elevation models along the Atlantic and Gulf of Mexico coasts of the United States. (a) Standard deviation (SD) of checkpoint density (points per km^2). SD of the proportion of each land cover class for (b) Upland grass/pasture, (c) Upland forest, (d) Upland shrub, (e) Palustrine emergent wetland, (f) Palustrine woody wetland, (g) Estuarine emergent wetland, (h) Barren, and (i) Developed classes. C-CAP land cover distribution can be visualized by U.S. state using the C-CAP Land Cover Atlas (https://coast.noaa.gov/ccapatlas/). For U.S. State abbreviation definitions see https://www.faa.gov/air_traffic/publications/atpubs/cnt_html/appendix_a.html.

within the 'Work Unit Extent Spatial Metadata (WESM)' geopackage (accessible at https://www.usgs.gov/3d-elevation-program/3dep-spatial-metadata). This metadata layer includes lidar acquisition dates, lidar Quality Levels (QL), and other metadata for acquisitions in 3DEP. Lidar data acquired for 3DEP is designed to meet the Lidar Base Specification (LBS), which includes specifications for lidar collection and standards for the results (NGP 2022). QL, defined in the LBS, is used to define classifications based on aggregate nominal pulse spacing, swath data, absolute vertical accuracy, and minimum DEM cell size. In terms of point spacing, QL 0, 1, 2, and 3 are defined by aggregate nominal pulse spacing of less than 0.35 m, 0.35 m, 0.71 m, and 1.41 m, respectively. This study did not include any QL0 data. One key difference between QL0 and QL1 is stricter absolute vertical accuracy requirements.

Vertical accuracy checkpoints collected by data contractors are sometimes included in the 3DEP products. These data are collected using GNSS receivers with collection methodologies expected to have at least twice the target accuracy of their final products and adhere to best practices on collecting checkpoints as outlined by the ASPRS (ASPRS 2023). The checkpoints used for assessing accuracy are independent from ground control points used for rectification.

Land cover information used in this study was from the National Oceanic and Atmospheric Administration's (NOAA) 10-m BETA Coastal Change Analysis Program (C-CAP; NOAA 2019) and is derived from 2015 to 2017 orthoimagery. Compared to other national land cover products, C-CAP provides detailed delineation of coastal wetlands by salinity (i.e., estuarine and palustrine wetlands) and vegetation type (i.e., herbaceous, shrub, and forested; Table 1). The distribution of land cover types within the study area is shown in Figure 1b-i. C-CAP land cover distribution can be visualized by U.S. state using the C-CAP Land Cover Atlas (https://coast.noaa.gov/ccapatlas/).

Table 1. Land cover classes used to assess the vertical accuracy of digital elevation models by coastal land cover types. Source data was the 2016 National Oceanographic and Atmospheric Administration's (NOAA) Coastal Change Analysis Program's (C-CAP) 10-m BETA land cover product (NOAA 2019). NA, Not applicable.

	Classes for our study	
NOAA C-CAP class	Simplified land cover	Vegetation state
Developed impervious	Developed	Non-vegetated
Upland Herbaceous	Upland grass/pasture	Vegetated
Upland Forest	Upland forest	Vegetated
Scrub/Shrub	Upland shrub	Vegetated
Palustrine Forested Wetland Palustrine Scrub/Shrub Wetland	Palustrine woody wetland	Vegetated
Palustrine Emergent Wetland	Palustrine emergent wetland	Vegetated
Estuarine Forested Wetland Estuarine Scrub/Shrub Wetland	Estuarine woody wetland	Vegetated
Estuarine Emergent Wetland	Estuarine emergent wetland	Vegetated
Barren Land Unconsolidated Shore	Barren	Non-vegetated
Open Water Palustrine Aquatic Bed Estuarine Aquatic Bed	Water	NA

2.2. Dataset collation

For this study, we developed a multistep workflow for collating and extracting information to vertical accuracy checkpoints provided by contractors. Spatial analyses in this study were completed using Esri ArcGIS Pro v. 3.0.3 (Redlands, CA). The first step in creating the checkpoint dataset was to extract checkpoint data from the 3DEP WESM. The WESM provides links to documents related to acquisition overview, checkpoints, flight logs, and other information that the contractor sends along with their lidar data. While checkpoints likely exist for all 3DEP acquisitions, we were not able to locate checkpoints for all lidar acquisitions (hereafter called 'work units'). From 163 work units, we found 60 sets of checkpoints spanning from 2012 to 2020. Checkpoints were provided either as Esri shapefiles, comma-separated value spreadsheets, or in tables within reports. Each of these file formats required a different type of manual processing to extract the checkpoint coordinates, elevation, and projection information. For Esri shapefiles, the only processing required was to standardize units, column names, and spatial reference. Microsoft Excel (Redmond, WA) was used to extract the appropriate columns from spreadsheets to obtain coordinates and elevations. For the text documents, we used Microsoft Excel Power Query to extract the table from the appropriate pages of the documents.

We were interested in assessing the accuracy of DEMs using only the checkpoints that were collected concurrently with the lidar data acquisition for that work unit. Ensuring each checkpoint was paired with the appropriate DEM elevation required careful processing. First, we projected points to the North American Vertical Datum of 1983 Albers Equal Area and generated coordinates in decimal degrees for each point. Rather than a time consuming and storage-intensive process of downloading DEMs for each of the 60 work units, we used the available 3DEP Image Server Query (accessible at elevation.nationalmap.gov/arcgis/rest/services/3DEPElevation/ImageServer/query) to return a list of DEM tile names that provide elevation coverage at the coordinates entered to the function, including older DEMs. We used Python package BeautifulSoup4.11.1 (Richardson 2022) and string-matching operations to extract a link to the matching DEM tile. If the matching DEM was not available in the query, we retrieved the original product resolution (OPR) DEM for the lidar work unit, which can vary in cell size (minimum 0.5 m, median 1 m, interquartile range 2.6 m, and maximum of 5 m). The OPR DEM is a product made by the contractor for 3DEP partner requirements and posted in USGS data storage sites. OPR elevation data were used for 1443 out of the final 5228 checkpoints. We ensured projection consistency and extracted DEM values to the checkpoints.

Upon collecting the appropriate DEM values, we collated the checkpoint datasets and calculated the elevation differences between the DEM and the checkpoints. Some work units extended outside of the study area and corresponding checkpoints were omitted from our study. We then joined the QL value from the WESM using the work unit ID.

For this study, NOAA's C-CAP data was simplified into two schemes (Table 1): 1) NVA or VVA and 2) simplified land cover. The simplified land cover reduced the 15 classes originally in the study area to a total of eight classes. Due to limits in spatial extent of the 10-m product, we omitted 757 unclassified points located in Texas, Virginia, New Jersey, and Pennsylvania.

2.3. Statistical analysis

We assessed accuracy by vegetation state (i.e., non-vegetated and vegetated), by simplified land cover, and by lidar QL. In accordance with ASPRS (2023), accuracy for non-vegetated areas, NVA, was represented by the root mean square error (RMSE; (Equation 1). The NVA represents accuracy when all non-vegetated classes were combined. Due to the non-normal distribution of vegetated error, the 95th percentile error was used for any class determined to be vegetated (Enwright et al. 2023). The VVA represents accuracy when all vegetated classes were combined. Equations (2) and (3) reflect Mean Error and Normalized Median Absolute Deviation (NMAD; Höhle and Höhle 2009), alternative measures of accuracy that we used to examine elements of bias and variability.

$$\mathrm{RMSE} = \sqrt{\Sigma \frac{(\Delta\ y)^2}{n}} \tag{1}$$

$$\text{Mean Error} = \Sigma \frac{\Delta y}{n} \tag{2}$$

$$\mathrm{NMAD} = 1.4826 \times \mathrm{median}(|\Delta y_i - \mathrm{median}(\Delta y)|) \tag{3}$$

where Δ y is the difference of DEM elevation and checkpoint observed elevation, n is the sample size, and Δy_i denotes the individual differences $i = 1, \ldots, n$. These statistics were calculated using the Python data analysis package Pandas (Pandas Development Team 2021).

3. Results and discussion

3.1. Vertical accuracy checkpoints distribution

Checkpoint density is dependent on both the quantity of lidar acquisitions in an area and the quantity and distribution of checkpoints that a contractor captured during an accuracy assessment. Figure 1a shows the checkpoint count by state and illustrates the distribution of checkpoints in the study area. The contractor checkpoints collated in this study with land cover classes and lidar quality information are available as a USGS data release (Han et al. 2024).

3.2. Accuracy results

Aggregating all the points as either non-vegetated or vegetated, we find accuracy values meet the latest ASPRS specifications for lidar (i.e., 10-cm NVA RMSE), which is the criterion for lidar standards (Table 2a). These metrics are similar to those that we would find for an individual acquisition, which suggests that the checkpoint collation process and the usage of external land cover may not have introduced discernable error.

Across QLs, NVA is similar, with a slightly higher accuracy for QL3. This discrepancy between expected accuracies in QLs could be due to low sample sizes or spatial distribution of checkpoints. The VVA has a 2-cm range with the highest accuracy in QL1. Similar to trends in NVA, the QL3 VVA is more accurate than QL2, which may also be due to the small sample size. VVA contributes to only 66 points out of the 120 points in QL3, and only 7 of

Table 2. Summary statistics for the vertical accuracy of digital elevation models along the U.S. Atlantic and Gulf of Mexico coasts using vertical accuracy checkpoints provided by contractors. (a) Statistics are provided for the non-vegetated vertical accuracy (NVA) and vegetated vertical accuracy (VVA) for pooled data and by Quality Level (QL). (b) Vertical accuracy by simplified land cover class. In alignment with ASPRS (2023), accuracy for NVA was represented by the root mean square error (RMSE), whereas vegetated error was represented using the 95th percentile error (95P) given the non-normal distribution of vegetated error (Enwright et al. 2023). *n*, sample count; ME, mean error; SD, standard deviation; NMAD, normalized median absolute deviation; NA, Not applicable.

	Accuracy metrics (cm)				Accuracy metrics (cm)					
Type	RMSE	95P	*n*	QL	RMSE	95P	ME	SD	NMAD	*n*
(a)										
NVA	6.9	NA	2520	QL1	7.1	NA	0.5	7.0	5.4	457
				QL2	6.9	NA	0.1	6.9	5.4	2009
				QL3	6.2	NA	−0.3	6.2	4.6	54
VVA	NA	22.3	2708	QL1	NA	19.9	5.4	10.4	8.2	562
				QL2	NA	22.9	3.9	29.6	8.6	2080
				QL3	NA	20.2	4.0	9.7	12.1	66

	Accuracy metrics (cm)					
Simplified land cover class	RMSE	95P	ME	SD	NMAD	*n*
(b)						
Barren	7.7	NA	2.0	7.5	6.0	298
Developed	6.8	NA	−0.1	6.8	5.3	2222
Estuarine emergent wetland	NA	33.8	12.9	11.8	11.5	36
Palustrine emergent wetland	NA	21.9	5.9	9.6	8.6	163
Palustrine woody wetland	NA	26.4	−3.9	65.4	10.8	112
Upland forest	NA	21.8	2.6	36.4	8.6	572
Upland grass/pasture	NA	21.6	4.6	11.1	8.3	1691
Upland shrub	NA	23.1	8.8	55.7	9.0	134

these are located within wetlands. Despite the limited sample size, the increase in VVA for QL1 May be due to better vegetation penetration with the higher pulse density. As more contractor checkpoint data become available, future efforts could reassess how these QLs compare in addition to looking at higher QL levels (e.g., QL0).

When assessing accuracy by land cover type (Table 2b), we found the non-vegetated classes (i.e., Barren and Developed) had similar RMSEs (within about 1 cm). For vegetated classes, Palustrine emergent wetlands, Upland forest, and Upland grass/pasture had similar error. Estuarine emergent wetland had the highest error with 95th percentile error of about 34 cm, which was lower than estimates from wetland-specific studies and reviews (Enwright et al. 2023; Medeiros et al. 2015). Although we see that the Palustrine woody wetland and Upland shrub classes had error that could arise from vegetation-related obstacles, we also see that the Palustrine emergent wetland class had low error despite expecting similar impacts on elevation error from hydrology and vegetation as in the Estuarine emergent wetland class. However, the small checkpoint sample size for this and several other classes reduces our confidence in these results, as we found that VVA was not representative of general vertical accuracy for all vegetated areas. For example, Estuarine emergent wetland (1% of checkpoints, 3% of land cover), Palustrine emergent wetland (3% of checkpoints, 5% of land cover), Palustrine woody wetland (2% of checkpoints, 18% of land cover), Upland forest (11% of checkpoints, 34% of land cover), and Upland shrub (3% of checkpoints, 4% of land cover) all have lower small sample sizes than their relative cover for the entire study area. Only 6% of checkpoints were classified as wetland, but 29% of land cover was classified as wetland. The lack of representation in locations such as wetlands could be due to limited site accessibility where hydrology, vegetation, and land ownership may reduce sample feasibility. A sample design that is spatially balanced and representative of all conditions is likely beyond the scope of work for contractor checkpoint creation. Although the guidance has evolved overtime, the latest ASPRS guidelines require 30 points in each NVA and VVA category with recommendations for additional points as study area increases above 1000 km^2 up to a max of 120 points for area for areas over about 9000 km^2. The standards call for checkpoints to be generally proportional across various vegetated land cover types within an acquisition area. In cases where this is not feasible, the guidelines suggest use of best professional judgement and agreement between the data producer and requester. Depending on research objectives, our study highlights the potential need for augmenting the contractor-provided accuracy information with site-specific in situ data collection and/or data from literature, as was done for coastal wetlands in Enwright et al. (2023).

Our methods built upon previous work by Gesch, Oimoen, and Evans (2014) by using updated data. Their study found wetlands to be a more accurate class, while our study found that using contractor checkpoints and higher resolution data resulted in wetlands being the least accurate class. The discrepancy of our findings could be due to spatial resolution of land cover data, DEMs, and lidar point spacing differences between the studies.

Expanding beyond RMSE, we found that checkpoints in Estuarine emergent wetland areas have larger positive mean error (i.e., DEM overestimates checkpoint elevation; Figure 2), which agrees with other studies that show that these areas have high bias (Enwright et al. 2023). Woody vegetation also had higher bias and high SD (Table 2b; Figure 2), a potential result of dense vegetation as an obstacle of lidar capture of ground elevation. NMAD is an outlier-resilient estimate of

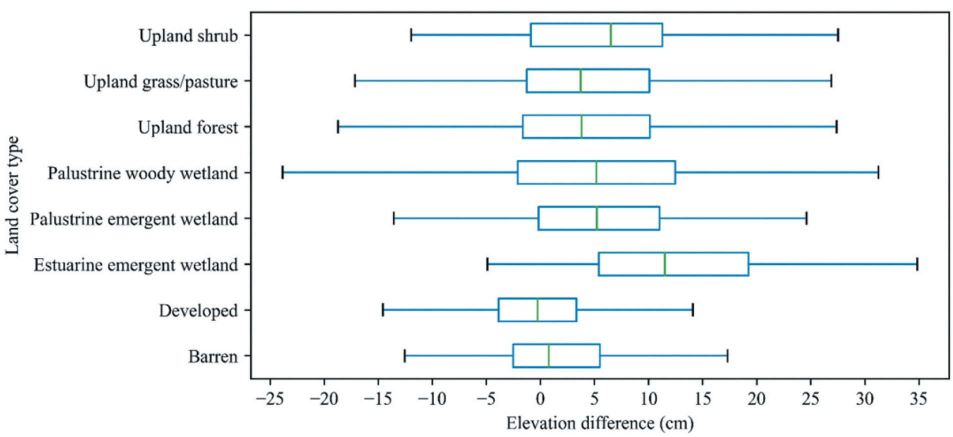

Figure 2. Boxplots of differences between elevation checkpoints and digital elevation models developed for the Atlantic and Gulf of Mexico coasts of the United States, grouped by land cover type.

standard deviation, and through comparison of the two, we can assess the effect of outliers on variability. NMAD and SD are similar for non-woody classes; however, we found differences between the metrics in all woody classes, which suggest that outliers have larger impact on the variability of errors for these classes. Knowledge of classes prone to high outlier effects highlight sample size as a consideration when assessing accuracy.

3.3. Improvements and applications

We anticipate future additions in 3DEP to increase the number of checkpoints available for QL1 DEMs. While this study focused on use of contractor checkpoints, this approach could be enhanced by using other published elevation data, including the National Geodetic Survey geodetic control points and a database of OPUS, and points collected for research studies, or long-term monitoring programs (Sharp et al. 2021). Due to coastal dynamics, the use of checkpoints with temporal differences with the DEM acquisition date could introduce error. There is also capacity for improvements in land cover data as maps like NOAA's C-CAP product become more readily available at higher spatial resolution. Future studies could consider using a fuzzy approach to enhance the assessment of land cover-based accuracy to address potential issues with land cover uncertainty. While our study utilized C-CAP for the more detailed coastal wetland zonation, other efforts could explore utilizing other land cover datasets including, detailed local-level land cover or vegetation-type maps. These kinds of studies could investigate additional DEM accuracy factors such as slope gradient and more specific vegetation characteristics (e.g., canopy height), which could lead to different methods of grouping spatially explicit vertical accuracy measures, where sample size allows. Local studies could conduct detailed experiments to expand our understanding of the physical relationship between these factors and aerial lidar data collection. Building on research like Su and Bork (2006), future research could evaluate how contemporary manned airborne lidar systems are performing across a range of conditions in specific land cover classes.

Vertical accuracy has seen applications in mapping inundation and exposure to tidal datums (Amante 2019; Enwright et al. 2023; Gesch 2018). Gesch (2018) reviewed how vertical error has applications in elevation-based assessments of inundation areas or sea level rise increment estimations. Monte Carlo error propagation is a method for accounting for data uncertainty (Amante 2019; Enwright et al. 2023). These approaches require information about elevation error, which can be provided by a study like this, especially information related to land cover-based elevation error. Results from our study could be used to provide enhanced information for general elevation accuracy metrics such that Monte Carlo and other methods could use metrics specific to the land cover and QL classification to estimate the accuracy of the DEM on a per pixel basis (Amante 2018). Finally, a more nuanced discussion of the limitations to general accuracy assessments reported in lidar-derived DEM metadata may help researchers and natural resource managers gauge when and where additional data should be collected for a more robust understanding of vertical accuracy.

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Disclosure statement

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