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Data Descriptor

Removal of Positive Elevation Bias of Digital Elevation Models for Sea-Level Rise Planning

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Abstract: Digital elevation models (DEMs) based on LiDAR surveys provide critical information for predicting the vulnerability of coastal areas to sea-level rises. Due to the poor penetration of LiDAR pulses in marsh vegetation, bare-earth DEMs for coastal wetlands are often subject to positive elevation bias, and thus underestimate vulnerability. This data publication includes comprehensive elevation surveys from seven coastal wetlands in coastal New Jersey, and an evaluation of the accuracy and positive elevation bias of each publically available DEM. Resampling the DEMs at a coarser resolution, replacing cell values using the minimum value in a wider search window (4 m), removed this positive elevation bias with no loss of accuracy.

Dataset: The following are available online at http://www.mdpi.com/2306-5729/4/1/46/s1.

Keywords: LiDAR; post-processing; coastal marsh; signed error

1. Summary

The rate of global sea-level rise (SLR) has increased abruptly, relative to stable Late Holocene rates of 0.5–1.0 mm yr^{-1} that have prevailed over the last 2000 years [1,2], to 1.7 ± 0.3 mm·yr^{-1} during the 20th century [3] and 3.1 ± 0.3 mm yr^{-1} since 1993 [4]. These rates of SLR are associated with trends in increasing temperature [5,6], and studies have generally concluded that statistically significant SLR acceleration is occurring [4]. Although there is significant variability by region in projected SLR rates, global rates by 2100 predicted by the IPCC AR5 report ranged from 28–61 to 52–98 cm, depending on emission scenarios. SLR will impact millions of coastal residents over the coming decades [7] and there is a strong need for accurate elevation models to characterize vulnerability to SLR for both the built environment, as well as coastal habitats such as dunes, beaches, and wetlands, which can act as natural defenses against SLR.

Coastal wetlands can protect coastal communities from event-based flooding, which is amplified by SLR [8]. However, they are themselves quite vulnerable to climate change, as their sustainability depends on the interplay between organic soil formation and sediment deposition relative to SLR rates [9]. If marshes can build up faster than the sea rises, they will be sustainable. If SLR exceeds accumulation rates, marshes will drown, and in this context, millimeters matter [9]. Although digital elevation models derived from light detection and ranging (LiDAR) surveys can be as accurate as typical GPS ground surveys (± 5 cm), the presence of thick vegetation in coastal wetlands obstructs the ground surface, leading to positive elevation biases that can result in underestimations of climate change vulnerability [10].

This dataset includes elevation data surveys (~3200 points) from seven New Jersey coastal wetlands, and was collected to ascertain the level of positive elevation bias found in digital elevation models (DEMs). We found that positive elevation biases (measured as signed error) ranged up to 0.3 m, which could significantly affect assessments of wetland vulnerability to SLR (Table 1). Post-processing DEMs using a minimum bin method largely removed positive elevation biases with minimal losses in accuracy (Figure 1). We found that resampling the DEM at 4 m resolution using the minimum bin method resulted in no loss of accuracy as measured by root mean square error (RMSE), but reduced the signed error from an average of 12 to 1.5 cm. Resampling at 5 m resolution increased the RMSE from 21 to 23 cm, and shifted the signed error to a negative elevation bias of −1.0 cm.

Table 1. Vertical elevation differences for the as-received LiDAR vs. topographic surveys.

Site Name	DEM [1]	No. of Points	RMSE (cm)	Signed Error (cm)	25th Quartile (cm)	75th Quartile (cm)
Crosswicks Creek	2015 USGS	572	22.1	−4.59	−14.4	−1.3
Dividing Creek	2015 USGS	875	27.3	13.9	2.62	19.6
Maurice River	2015 USGS	162	19.4	16.8	11.0	22.7
Dennis Creek	2014 NOAA	223	27.0	24.8	17.4	30.3
Dennis Creek	2015 USGS	223	35.7	28.6	16.7	35.8
Reedy Creek	2014 NOAA	329	11.7	8.79	3.75	13.2
Reedy Creek	2015 USGS	329	12.5	7.48	2.03	10.1
Island Beach	2013 USACE	294	13.9	9.35	1.55	14.7
Island Beach	2014 NOAA	294	9.87	7.40	2.91	10.6
Island Beach	2015 USGS	294	14.9	7.18	1.62	8.33
Channel Creek	2010 ARRA	697	22.7	11.4	1.38	10.9
Channel Creek	2013 USACE	697	31.2	24.0	12.3	26.3
Channel Creek	2014 NOAA	697	20.9	10.4	4.34	14.9
Channel Creek	2015 USGS	697	25.8	5.90	-1.36	7.60

[1] See Table 3 and metadata for full explanation of digital elevation models (DEMs).

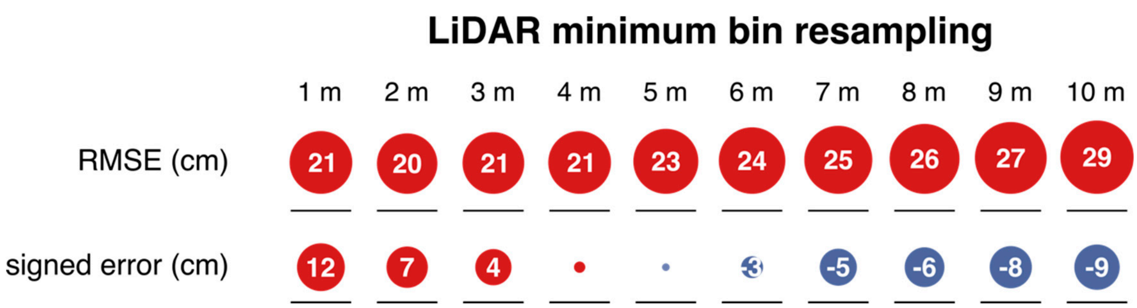

Figure 1. Comparison of RMSE and signed error for DEMs resampled using the minimum bin method.

However, several of the DEMs we worked with did not conform to this trend and maintained a positive elevation bias even after post-processing (Figure 2), such as the 2013 DEM covering the research site at Channel Creek and the 2015 DEM covering Dennis Creek. In such cases, it may be more beneficial to use masks, potentially based on plant cover class, to improve DEM accuracy. This method has been used widely in coastal wetlands outside the Northeastern U.S., where the plant cover is found throughout the year (e.g., [11]). In the Northeast, by collecting LiDAR data in spring leaf-off conditions when the vegetation cover is sparse, the need for masks has largely been avoided.

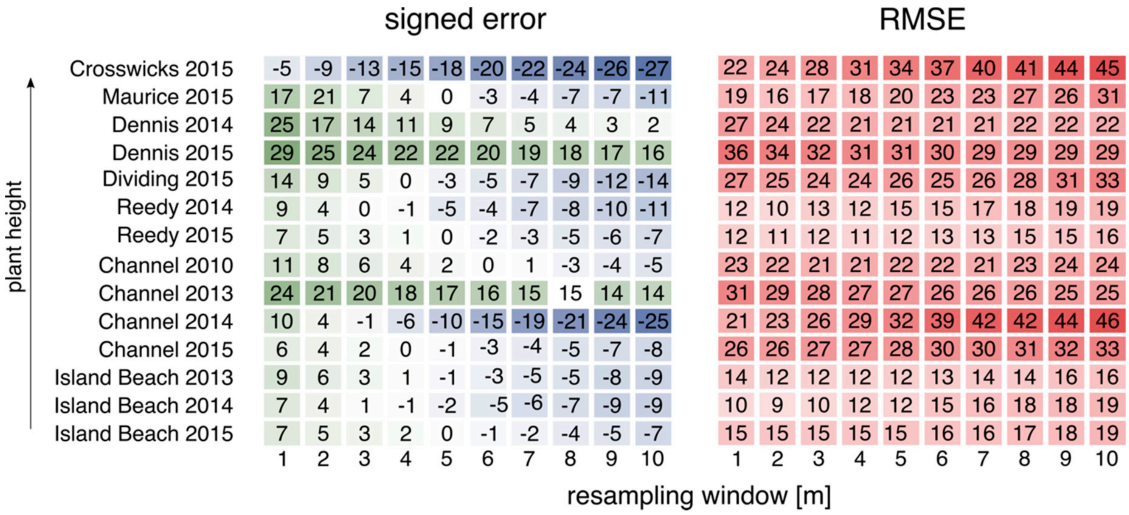

Figure 2. Comparison of RMSE and signed error for resampled DEMs (in cm).

By publishing this dataset, we intend for it to be used to guide DEM post-processing and to develop new DEM post-processing methods relevant to predicting impacts of sea-level rise in vegetated coastal areas. Future work using this data will include validating and applying SLR models for predicting coastal wetland vulnerability to climate change.

2. Data Description

2.1. Elevation Survey Points

Shapefiles of surveyed elevation points are provided for each individual study site (Table 2). These shapefiles consist of an elevation field, where the elevations are given in meters relative to the NAVD88 datum, GEOID12A. Elevation surveys were conducted between 2014 and 2018. A data inventory is provided (Supplementary Material, File 1).

Table 2. Surveyed locations in New Jersey coastal wetlands (Supplementary Material, File 2).

Site Name	Location	Salinity	Vegetation Height (m)
Crosswicks Creek	40°9.76′ N, 74°42.51′ W	0.10‰	1.2 m
Dividing Creek	39°14.14′ N, 75°6.76′ W	16.7‰	0.32 m
Maurice River	39°15.95′ N, 74°59.72′ W	11.2‰	0.56 m
Dennis Creek	39°10.58′ N, 74°51.74′ W	15.9‰	0.34 m
Reedy Creek	40°1.74′ N, 74°5.07′ W	20.2‰	0.29 m
Island Beach	39°47.96′ N, 74°6.10′ W	26.8‰	0.17 m
Channel Creek	39°37.43′ N, 74°16.20′ W	25.6‰	0.23 m

2.2. Digital Elevation Model Metadata

Metadata is provided for the publically available DEMs analyzed as part of this study (Supplementary Material, File 3), following the Content Standard for Digital Geospatial Metadata: Extensions for Remote Sensing Metadata, FGDC-STD-012-2002. For each site, all publically available DEMs were analyzed, which ranged from one to four DEMs per study site (Table 3). For all DEMs, the initial resolution was 1 m, although DEMs were resampled and analyzed at a coarser resolution. A data inventory is provided (Supplementary Material). The 2010 DEM was adjusted from the GEOID09 to GEOID12A. The 2015 United State Geological Survey (USGS) topobathy DEM covers all of New Jersey and Delaware coastal areas, and consists of the best available multi-source topographic and bathymetric elevation data, integrating over 89 different data sources, including topographic and bathymetric LiDAR point clouds, hydrographic surveys, side-scan sonar surveys, and multi-beam surveys from various federal, state, and local agencies.

Table 3. Topobathy DEMs analyzed by this study.

Site Name	Digital Elevation Model	Resolution	Date	Sensor
Crosswicks	2015 USGS CoNED	1 m	multiple years	multiple sensors
Dividing	2015 USGS CoNED	1 m	multiple years	multiple sensors
Maurice	2015 USGS CoNED	1 m	multiple years	multiple sensors
Dennis	2014 NOAA Post-Sandy	1 m	Nov 2013–June 2014	Riegl VQ-820G
Dennis	2015 USGS CoNED	1 m	multiple years	multiple sensors
Reedy	2014 NOAA Post-Sandy	1 m	Nov 2013–June 2014	Riegl VQ-820G
Reedy	2015 USGS CoNED	1 m	multiple years	multiple sensors
Island Beach	2013 USACE NCMP	1 m	Sept 2013–Oct 2013	CZMIL (USACE)
Island Beach	2014 NOAA Post-Sandy	1 m	Nov 2013–June 2014	Riegl VQ-820G
Island Beach	2015 USGS CoNED	1 m	multiple years	multiple sensors
Channel	2010 ARRA	1 m	Apr 2010	Leica ALS60 MPiA
Channel	2013 USACE NCMP	1 m	June 2013	CZMIL (USACE)
Channel	2014 NOAA Post-Sandy	1 m	Nov 2013–June 2014	Riegl VQ-820G
Channel	2015 USGS CoNED	1 m	multiple years	multiple sensors

3. Methods

Elevation surveys were conducted in seven separate New Jersey (USA) coastal wetlands at long-term monitoring locations (https://www.macwa.org), using real-time kinematic GPS receivers (a Leica Viva GS14 GNSS Receiver and Viva CS15 field controller, or a Trimble R6 GNSS receiver and TSC2 data controller) to assess the vertical accuracy of bare-earth DEMs based on LiDAR surveys. Data collection followed National Geodetic Survey guidelines for the RT3 accuracy class (0.04–0.06m horizontal precision; 0.04–0.08 vertical precision): Baselines < 20 km and collection at 1 s intervals for 15 s, with a steady fixed height rover pole without use of a bipod [12]. Study sites were located in Barnegat Bay and Delaware Bay, New Jersey, USA (Table 2; Figure 3). Mean vegetation height and salinity were found to vary quite widely across study sites [13], with strong co-variance between salinity and the height of marsh vegetation, with lower salinity wetlands supporting taller marsh vegetation ($r^2 = 0.89$, $p = 0.001$). Elevation surveys were conducted between 2014 and 2018. Surveyed points were downloaded from data controllers, and converted to point shapefiles (Supplementary Materials, File 2).

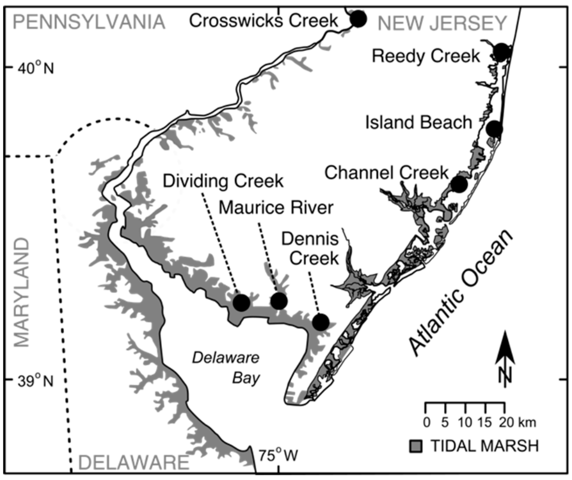

Figure 3. Location of elevation surveys and LiDAR comparisons.

All publically available DEMs available for research sites were obtained (Table 3). To assess differences in elevation between the two datasets, points were intersected with as-delivered DEMs, as well as DEMs post-processed using the minimum bin method [14]. The minimum bin technique selects the lowest point in a cell to represent the grid or raster value, increasing the search window from two to ten meters. DEMs were then resampled at coarser resolutions (2–10 m) using the aggregate function, replacing elevation values with the minimum value of the wider search window. Elevation differences between datasets were again measured using point-DEM intersections. Geospatial analyses were conducted in ArcGIS ver. 10.5.

Supplementary Materials: File 1. Data Inventory. File 2. Coastal wetland elevation survey: Shapefile of elevation points; File 3. DEM metadata.

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