CoastalDEM v2.1: A high-accuracy and high-resolution global coastal elevation model trained on ICESat-2 satellite lidar

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In Brief
In 2018, Climate Central released CoastalDEM v1.1, a near-global coastal digital elevation model (DEM) that used an artificial neural network to reduce errors present in a DEM derived from NASA's Shuttle Radar Topography Mission (SRTM). CoastalDEM v1.1 was tested against lidar-derived elevation data in the US and Australia, and showed greatly reduced vertical bias and root mean square error (RMSE) compared to SRTM in both forests and cities.

Here we present CoastalDEM v2.1, the newest version of Climate Central's digital elevation model. We have made a number of substantial improvements to our neural network architecture, input datasets, and training data, resulting in a DEM that outperforms not only SRTM and CoastalDEM v1.1, but all leading, publicly-available, global-scale models tested. This is especially true in low-lying and densely populated areas, which are most important for assessing coastal vulnerability, but also where most DEMs struggle due to the presence of tall buildings.

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1. Introduction

Accurate elevation data is essential to accurately assess the vulnerability of coastal communities to threats from sea level rise (SLR) and coastal flooding. While a few developed countries, such as the US, Australia, the UK, and others in Europe, have released high-quality elevation data derived from airborne lidar, most of the rest of the world, particularly in developing countries, relies on lower-accuracy global digital elevation models (DEMs) derived from satellite radar. These DEMs suffer from large vertical errors with a positive bias [1, 2]—especially in densely populated areas, where accurate vulnerability statistics are most important, but where satellite radar sensors see building tops as hills and mountains [3, 4, 5].

In recent years, efforts have been made to improve global elevation models by predicting and reducing their errors, though most attempts have either covered a very small area [6, 7] or only sought to reduce bias in vegetated areas, rather than cities [8, 9, 10, 11]. CoastalDEM v1.1 [2] was the first global-scale DEM that used an artificial neural network to correct errors present in NASA's SRTM. We tested this model against lidar-derived elevation data in the US and Australia, and found it greatly improved vertical bias and RMSE compared to SRTM in both forests and cities. However, as version 1.1 was trained on ground truth data in the US alone, and despite its high performance in Australia, there must be less confidence in its accuracy in areas with dissimilar vegetation, architecture, and population density.

Ideally, an error-correcting model would instead use high-quality globally-available ground truth data to train the model. However, at the time CoastalDEM v1.1 was generated, the best available candidate global dataset was ICESat, which was a 2003-2010 NASA satellite mission that, among other objectives, collected elevation profile measurements at points along straight lines across Earth's surface using a single laser altimeter beam (satellite lidar). These points had a large footprint (70 m) and were about 170 m apart along the linear tracks [12]. These data were also noisy, suffering from a multi-meter positive bias in certain terrain types, including forests [13]. While useful to help validate global elevation models, the data from the first ICESat mission were not suitable for use in training a neural network.

In late 2018, NASA launched the ICESat-2 mission, which promised much more dense and accurate land elevation measurements compared to its predecessor. Specifically, ICESat-2 features 6 beams (in 3 pairs, spaced 3 km apart) and gives elevation values every 100 m along track (each value is based on an algorithmic assessment of multiple photon measurements within each 100 m segment). [14]. Additionally, ICESat-2 computes vegetation height at every point, largely reducing this source of error, though no such correction is performed for urban structures. Early validation results [15, 16] suggest ICESat-2 terrain measurements contain vertical bias of less than 10 cm, and

RMSE less than 1 m, though these studies do not investigate performance in urban areas.

2. Technological Advances in CoastalDEM v2.1

- **Trained on high-quality global elevation data.** CoastalDEM v1.1 was trained using airborne lidar-derived elevation models in the US alone, which risked overfitting the model. CoastalDEM v2.1 is trained using data from NASA's recent ICESat-2 mission [14], which covers land across the entire world. This choice was aimed at further improving performance in other countries where architecture and population density can be very different than what exists in the US.
- **More accurate base elevation.** CoastalDEM v1.1 was based off of NASA's SRTM v3.0, whose errors were particularly severe with a >2 m positive bias and >4 m RMSE. CoastalDEM v2.1 instead uses NASA's recently-released NASADEM dataset, a more accurate reprocessing of SRTM's source data [17]. This gives CoastalDEM v2.1 a better "starting point" from which improvements are made.
- **Wider input elevation range.** CoastalDEM v1.1 only considered pixels whose SRTM elevation lies between 1-20 m. CoastalDEM v2.1 instead predicts corrections for all pixels on land between -10 m and 120 m. This choice was aimed at improving results both in low, flat regions with areas of negative vertical error due to random noise, as well as locations with tall skyscrapers that cause errors exceeding 20 m.
- **Larger and more sophisticated convolutional neural network (CNN) architecture.** CoastalDEM v1.1 used a small and multilayer perceptron neural network with 40 hidden units to predict errors present in SRTM. CoastalDEM v2.1 employs a far larger CNN with many thousands of hidden units, which is better suited to learn the highly nonlinear relationships between each of the input variables and the actual elevation.
- **New and updated input variables.** CoastalDEM v1.1 used a total of 23 input variables, including SRTM elevation, population density, and vegetation density. Since then, we have acquired more accurate versions of many of these datasets (such as NASADEM and WorldPop [18]), as well as added new ones. In addition, the convolutional neural network architecture allows us to utilize large input windows about each target, effectively resulting in over a thousand input variables for each pixel. These give the neural network much more context for each location to better improve predictions and reduce errors.

3. Results

3.1 Validation against ICESat-2

Here we use land elevation measurements from NASA's ICESat-2 as ground truth to assess the global accuracy of global DEMs. We include the six most-recently released products – CoastalDEM v2.1, CoastalDEM v1.1 [2], NASADEM [17], TanDEM-X [19], MERIT [8], and AW3D30 [20]. We assess each of the DEMs at their native horizontal resolutions, including CoastalDEM v1.1 at 1 arc-second. We disregard all ICESat-2 points flagged as being covered by clouds or snow. Additionally, all error values exceeding 50 m are treated as outliers and removed from the assessment (fewer than 0.005% of points have a discrepancy this large).

We have empirically found that DEM performance varies by elevation. Since CoastalDEM's intended purpose is for coastal flood modeling on land presently above sea level especially in populated areas, we primarily focus on land between 0-5 m relative to the EGM96 geoid (spanning the range of most storm and projected sea-level rise scenarios through the year 2100 [21, 22]), and where population density exceeds 1,000 people per square kilometer. More specifically, when assessing vertical accuracy of a DEM, we consider only grid cells where the "true" (ICESat-2) *or* the "estimated" (DEM) elevations are greater than zero and lower than the given maximum elevation (most often, 5 m). For brevity, for the rest of this report we only list the upper elevation bounds assessed (<5 m, <10 m, or <20 m), with the lower bound of 0 m left implied. All available data points present in ICESat-2 that meet the above requirements and given filters are used in the following assessments.

In the whole of the <5 m elevation band (including all areas, regardless of population density), the 30 m version of CoastalDEM v2.1 virtually eliminates global median bias to less than 0.01 m, contains an RMSE of 2.63 m, and LE90 (90th percentile linear error) of 2.99 m (Table 1), and outperforms the other global DEMs by a considerable margin. CoastalDEM v1.1 is found to contain errors with a slight negative bias. The updated CoastalDEM corrects that observed bias, while also reducing RMSE/LE90 by 20-50% compared to its competitors. CoastalDEM v2.1 thus shows the highest global accuracy when evaluated with these criteria.

In coastal areas with at least moderate development (greater than 1,000 people per square kilometer, where roughly half of the world's total population lives [18]) and in the elevation range at greatest risk from tides, storms and sea level rise (<5 m), mean vertical bias improves by more than 80%, from -0.5 m with CoastalDEM v1.1 to -0.1 m with CoastalDEM v2.1. These results reflect bias reductions from 91-95% compared to the other comparable DEMs, while maintaining RMSE/LE90 improvements of 20-40%. In segments of coastline with very high population density (greater than 10,000 people per square km, where errors caused by tall buildings are most severe) and the same elevation range (<5 m), CoastalDEM v2.1 contains a slightly positive bias, though still outperforms CoastalDEM v1.1 by 20%, and other DEMs by 80%.

At higher elevations (<20 m), CoastalDEM v2.1 contains slightly elevated errors, with a negative bias at about -0.2 m across all population densities. However, even here, CoastalDEM v2.1's median bias, RMSE, and LE90 outperform each of the other global DEMs. Across the board, performance at <10 m falls between the <5 m and <20 m results.

DEMs can contain spatially-autocorrelated errors even when they exhibit strong global performance, so it is important to also assess bias and RMSE at smaller spatial scales. Here we employ the GADM 2.0 dataset [23], a collection of global administrative units, to assess error distributions across regions. These distributions are computed at the smallest-available units by binning error values between -50 m to +50 m at 0.01 m intervals, which are added and aggregated to estimate error distributions at wider spatial scales, including across countries. We then use these binned distributions to estimate all relevant error metrics, including the median and LE90. Detailed error statistics by nation are presented in Supplementary Dataset S1.

Importantly for more local applications, CoastalDEM's performance is strong across most nations. In Figures 1 and 2, we present choropleth maps of nations' median biases and RMSE's under CoastalDEM v2.1, as well as TanDEM-X and MERIT. These maps only consider areas with at least moderate population density (more than 1,000 people per square kilometer) and below 5 m elevation. Only countries with at least 1,000 pixels meeting these requirements ($n \geq 1000$) are shaded. Under these metrics, CoastalDEM v2.1 consistently outperforms other global DEMs, with median bias lower in 90% of countries, and RMSE lower in at least 78% of countries. This is particularly notable in Asia and South America, which contain large populations near the coastline, and in many cases do not have lidar-derived elevation models available. National-level error statistics are available in Supplementary Dataset 1.

Figure 3 provides further evidence of consistent performance across small spatial scales. Here we assess error across smaller ('level 1") administrative units, roughly equivalent to US counties. We applied the same domain filtering as the preceding figures (>1,000 people per square kilometer, <5 m elevation). This figure presents median bias and RMSE density plots based on all (roughly 1,000 in count) of these small regions. Results for each of the global DEMs are represented by the colored curves, with steeper curves closer to 0 m corresponding to more consistent and accurate results. Again we find CoastalDEM v2.1 outperforms each of the competing DEMs, especially in terms of median bias.

Elevation profiles in select cities comparing ICESat-2, CoastalDEM v2.1, TanDEM-X, and MERIT are presented in Figures 4 and 5. We can see more clearly here that ICESat-2 is an imperfect truth set, especially in such densely populated areas - there are substantial noise and "spikes" in these measurements that can exceed tens of meters. That said, CoastalDEM v2.1's profiles generally do a better job than the other DEMs in following ICESat-2's curves. In fact, CoastalDEM appears to generate an even smoother elevation profile than ICESat-2. CoastalDEM v2.1's increasingly negative computed bias at higher population densities may not reflect true bias, but rather may be explained at least in part by the possibility that ICESat-2 has increasingly positive bias with density.

Table 1. Global error statistics across each DEM, three elevation thresholds (5 m, 10 m, and 20 m), and three population density bands (any density (Any), more than 1,000 people per km^2 (>1K), and more than 10,000 people per km^2 (>10K)). ICESat-2 is used as ground truth. For each row, only pixels are included whose elevation falls below the elevation threshold (according to ground truth or the DEM), and whose population density falls within the given band. Rows presenting CoastalDEM v2.1 statistics are in bold. All units are in meters except for population density, which is people per km^2.

DEM	Max Elev	Pop Density	Mean Bias	Median Bias	RMSE	LE90
CoastalDEM v2.1	**5**	**Any**	**-0.03**	**0.00**	**2.63**	**2.99**
CoastalDEM v1.1	5	Any	-0.06	-0.45	4.02	4.24
NASADEM	5	Any	1.59	0.66	4.65	6.40
TanDEM-X	5	Any	1.81	0.31	4.67	6.43
MERIT	5	Any	1.46	1.26	3.39	4.00
AW3D30	5	Any	2.41	1.43	5.54	7.97
CoastalDEM v2.1	**10**	**Any**	**-0.24**	**-0.12**	**2.89**	**3.39**
CoastalDEM v1.1	10	Any	-0.14	-0.62	4.42	4.75
NASADEM	10	Any	1.55	0.65	4.67	6.40
TanDEM-X	10	Any	1.74	0.29	4.63	6.43
MERIT	10	Any	1.43	1.26	3.46	4.11
AW3D30	10	Any	2.26	1.38	5.45	7.70
CoastalDEM v2.1	**20**	**Any**	**-0.33**	**-0.15**	**3.23**	**3.75**
CoastalDEM v1.1	20	Any	0.31	-0.45	4.83	5.73
NASADEM	20	Any	1.49	0.63	4.72	6.41
TanDEM-X	20	Any	1.72	0.30	4.78	6.65
MERIT	20	Any	1.41	1.27	3.71	4.36
AW3D30	20	Any	2.14	1.33	5.45	7.54
CoastalDEM v2.1	**5**	**>1K**	**-0.11**	**0.08**	**2.53**	**3.01**
CoastalDEM v1.1	5	>1K	-0.47	-0.29	3.01	3.81
NASADEM	5	>1K	1.21	1.01	3.56	5.29
TanDEM-X	5	>1K	1.81	1.35	3.21	4.89
MERIT	5	>1K	1.95	1.79	3.40	4.86
AW3D30	5	>1K	2.60	2.19	4.39	6.70
CoastalDEM v2.1	**10**	**>1K**	**-0.40**	**-0.14**	**2.79**	**3.33**
CoastalDEM v1.1	10	>1K	-0.70	-0.55	3.26	4.25
NASADEM	10	>1K	1.23	1.03	3.62	5.35
TanDEM-X	10	>1K	1.75	1.31	3.34	5.05
MERIT	10	>1K	1.89	1.76	3.51	4.90
AW3D30	10	>1K	2.58	2.19	4.41	6.71
CoastalDEM v2.1	**20**	**>1K**	**-0.47**	**-0.18**	**2.97**	**3.63**
CoastalDEM v1.1	20	>1K	-0.32	-0.45	3.59	4.92
NASADEM	20	>1K	1.27	1.07	3.69	5.44
TanDEM-X	20	>1K	1.74	1.31	3.44	5.11
MERIT	20	>1K	1.90	1.76	3.67	5.05
AW3D30	20	>1K	2.54	2.18	4.43	6.63
CoastalDEM v2.1	**5**	**>10K**	**-0.20**	**0.42**	**3.73**	**3.71**
CoastalDEM v1.1	5	>10K	-1.15	-0.52	4.83	5.57
NASADEM	5	>10K	2.05	2.01	4.74	6.76
TanDEM-X	5	>10K	2.85	2.59	4.21	5.93
MERIT	5	>10K	2.85	2.88	4.75	6.42
AW3D30	5	>10K	4.25	3.70	6.57	9.69
CoastalDEM v2.1	**10**	**>10K**	**-0.85**	**-0.07**	**4.40**	**4.78**
CoastalDEM v1.1	10	>10K	-1.19	-0.67	5.15	6.53
NASADEM	10	>10K	2.06	2.05	5.04	7.33
TanDEM-X	10	>10K	2.72	2.58	4.73	6.73
MERIT	10	>10K	2.66	2.83	5.11	6.96
AW3D30	10	>10K	4.40	3.80	6.88	10.37
CoastalDEM v2.1	**20**	**>10K**	**-1.09**	**-0.24**	**4.77**	**5.62**
CoastalDEM v1.1	20	>10K	-0.50	-0.38	5.48	7.84
NASADEM	20	>10K	1.99	2.04	5.34	7.76
TanDEM-X	20	>10K	2.60	2.54	5.08	7.25
MERIT	20	>10K	2.65	2.84	5.50	7.72
AW3D30	20	>10K	4.36	3.73	7.12	10.72

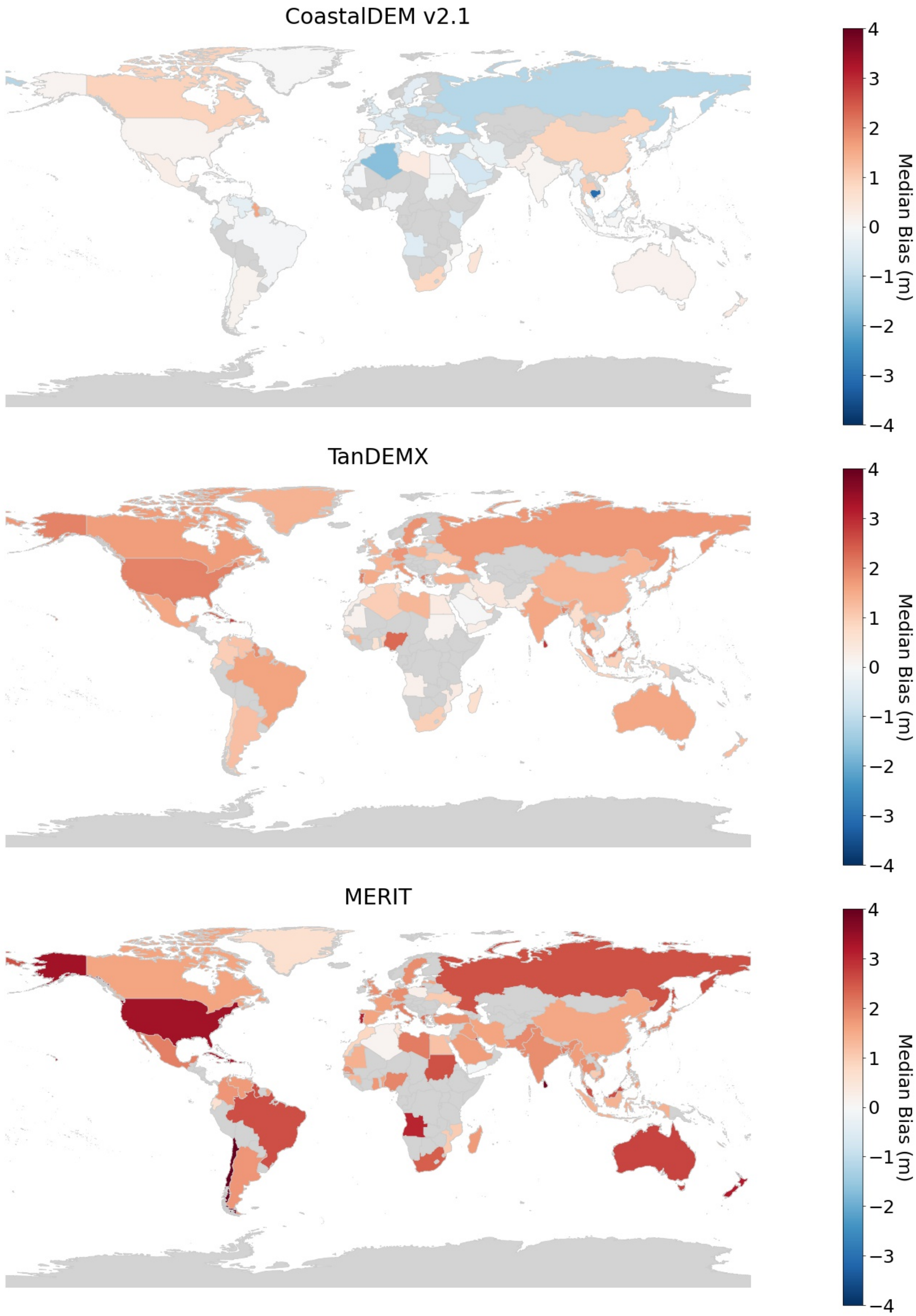

Figure 1. Choropleths presenting median bias under CoastalDEM v2.1, TanDEM-X, and MERIT in low-elevation regions across coastal nations, using ICESat-2 as ground truth. Only grid cells with elevation <5 m and population density >1000 people per km^2 are considered, and only nations with $n \geq 1000$ of these grid cells are evaluated.

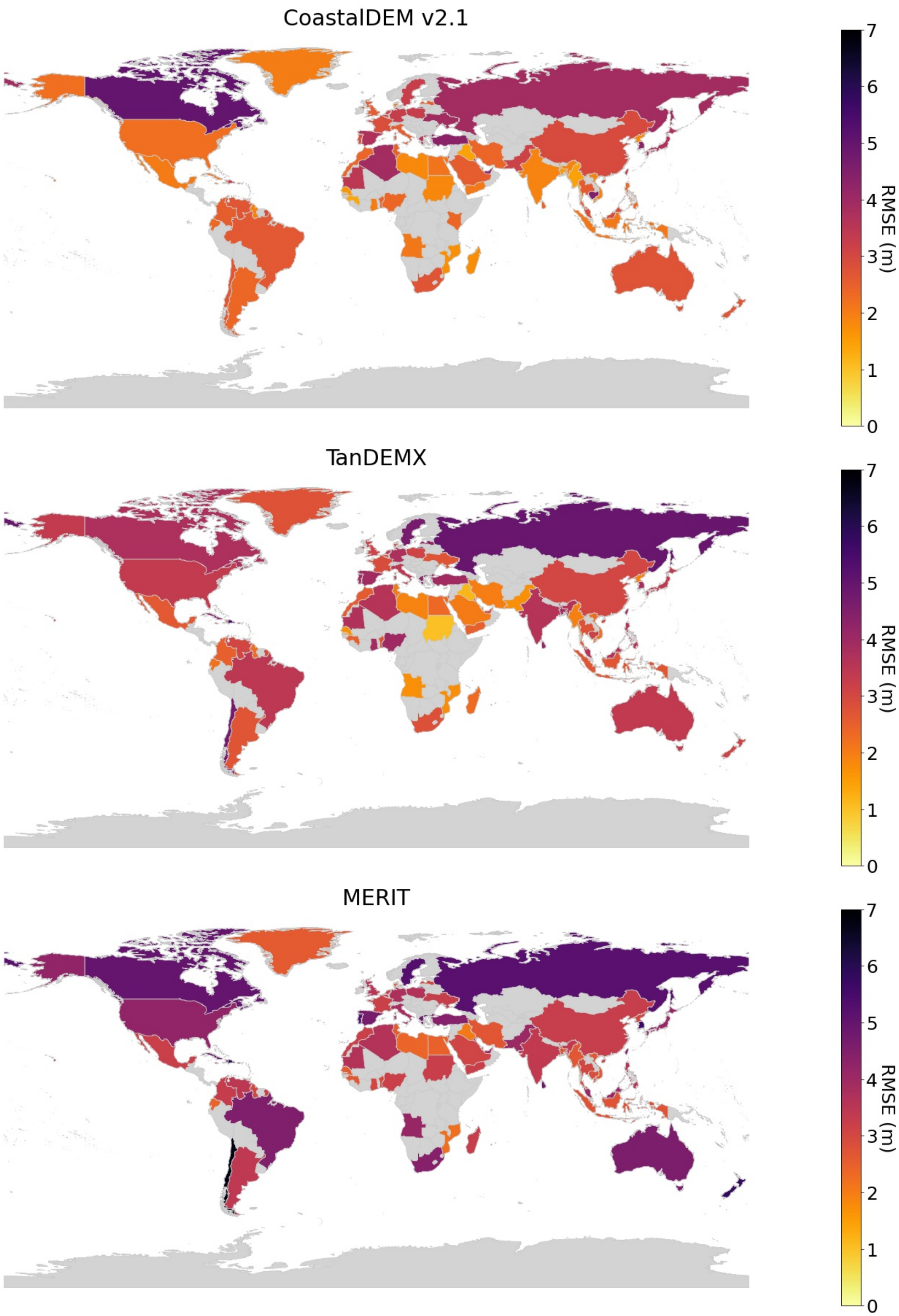

Figure 2. Choropleths presenting RMSE under CoastalDEM v2.1, TanDEM-X, and MERIT in low-elevation regions across coastal nations, using ICESat-2 as ground truth. Only grid cells with elevation <5 m and population density >1000 people per km^2 are considered, and only nations with $n \geq 1000$ of these grid cells are evaluated.

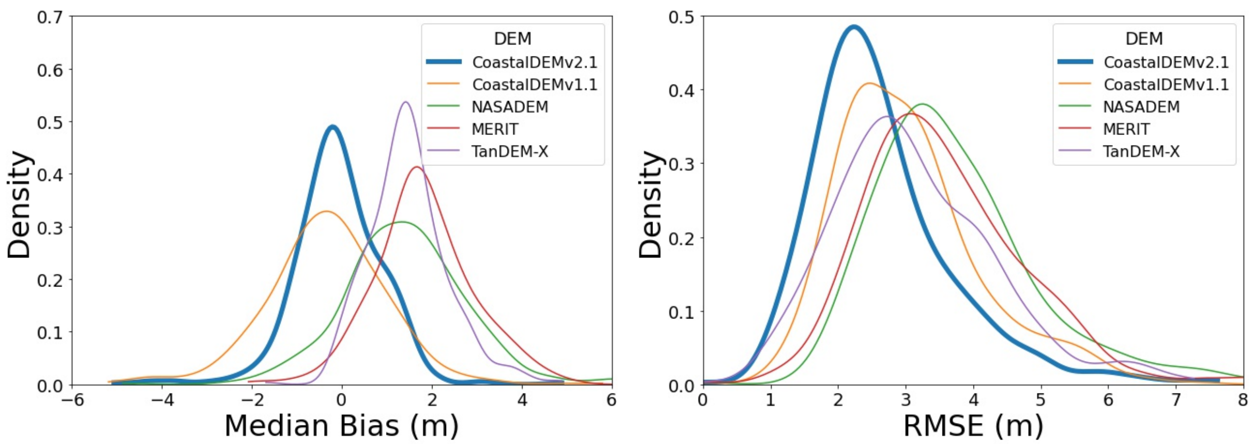

Figure 3. Density plots of median bias (left) and RMSE (right) for each of the global DEMs across level-1 administrative units (GADM 2.0), using ICESat-2 as ground truth. CoastalDEM v2.1 is highlighted in blue. Only grid cells whose elevations are lower than 5 m and contain >1000 people per square km are considered.

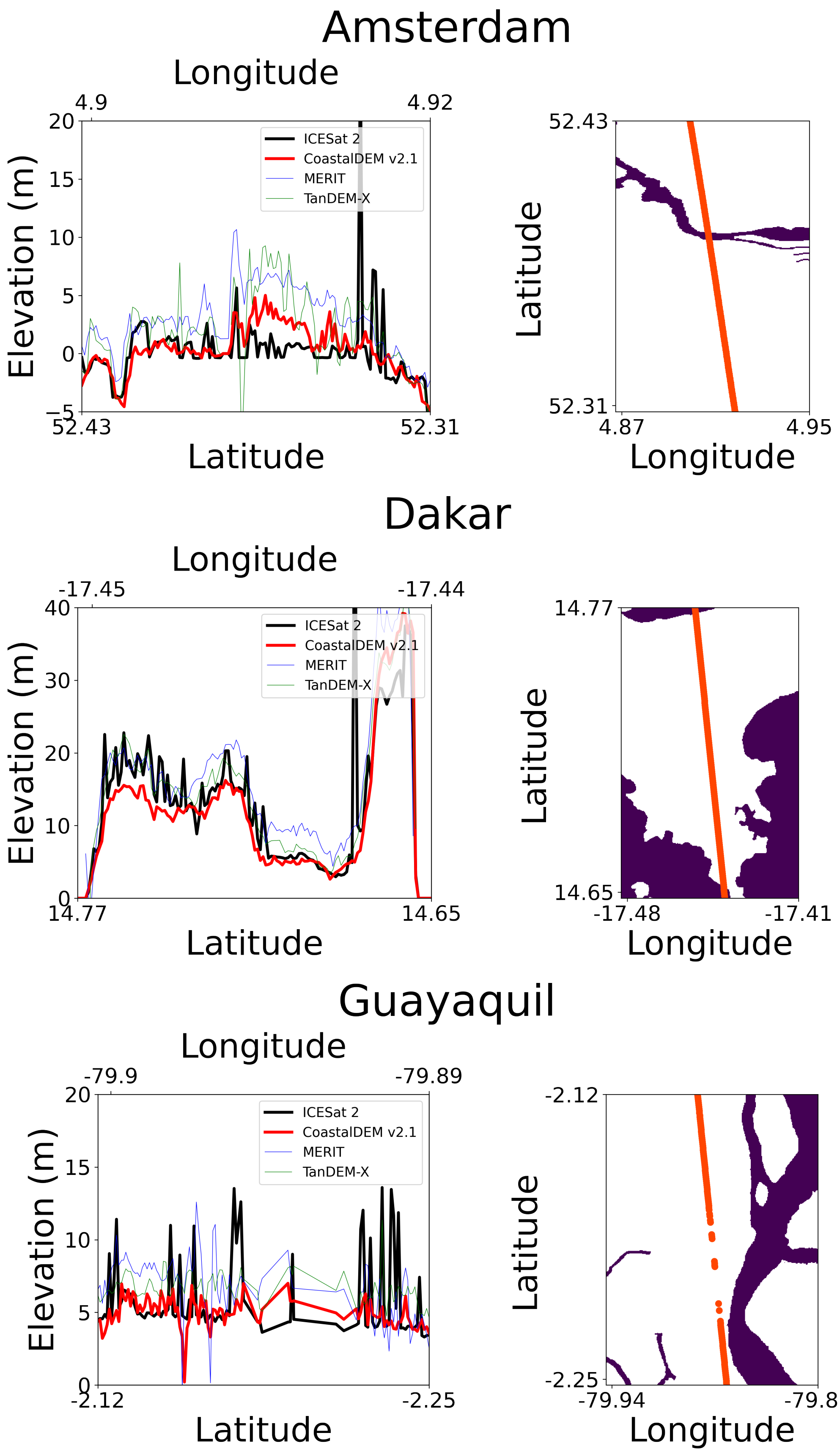

Figure 4. Elevation profiles under CoastalDEM v2.1, TanDEM-X, MERIT, and ICESat-2 in Amsterdam, Dakar, and Guayaquil along an ICESat-2 beam path. For each city, the left panel presents estimated elevation along the path according to each dataset, with ICESat-2 and CoastalDEM v2.1 highlighted in black and red, respectively. The right panel shows a map view where the path lies on the city in red, with water bodies highlighted in purple.

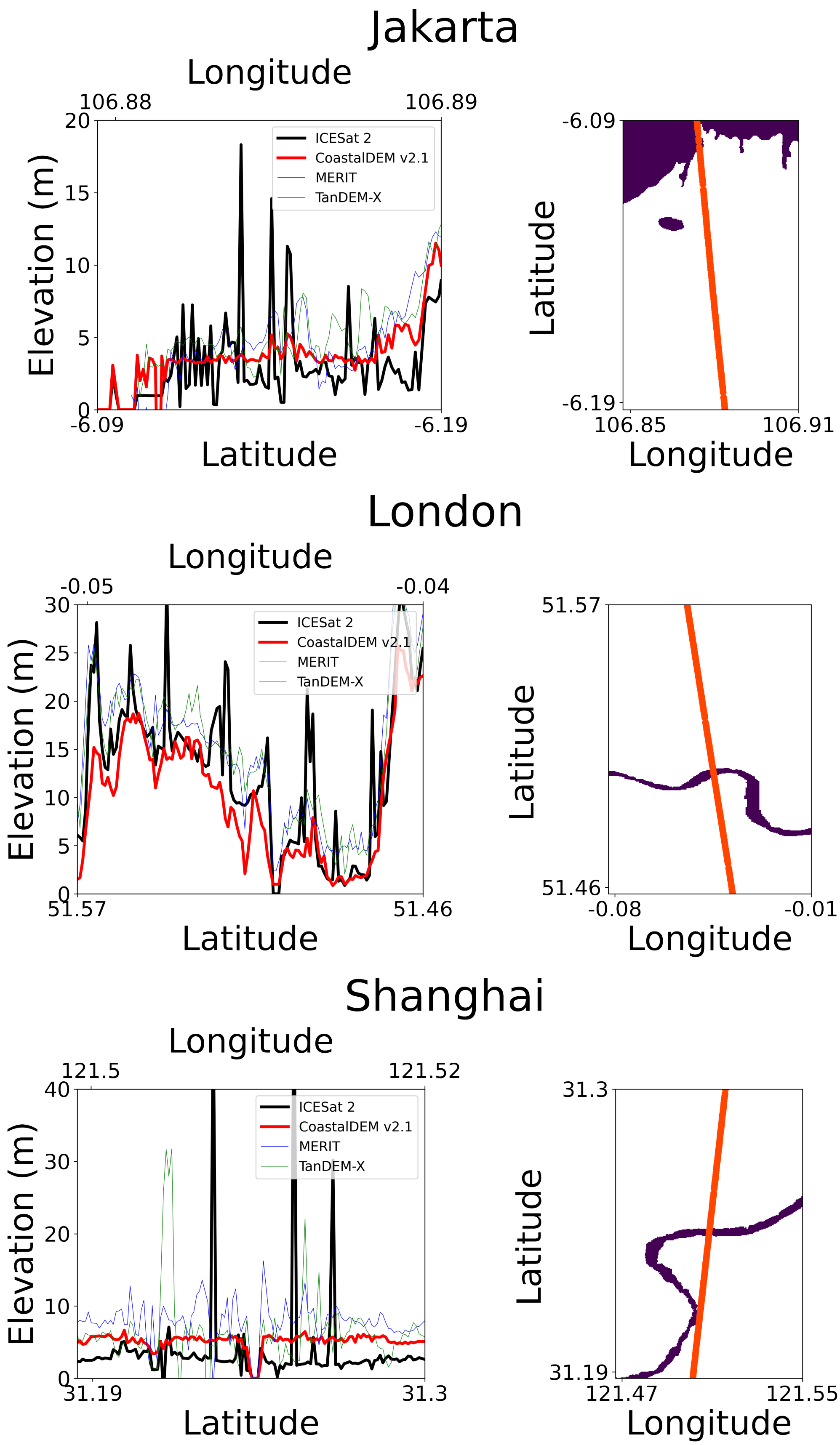

Figure 5. Elevation profiles under CoastalDEM v2.1, TanDEM-X, MERIT, and ICESat-2 in Jakarta, London, and Shanghai along an ICESat-2 beam path. For each city, the left panel presents estimated elevation along the path according to each dataset, with ICESat-2 and CoastalDEM v2.1 highlighted in black and red, respectively. The right panel shows a map view where the path lies on the city in red, with water bodies highlighted in purple.

3.2 Validation against airborne lidar-derived DEMs

While ICESat-2 is the best global elevation data source presently available, the fact that we train the CNN using it as ground truth means we risk misstating accuracy if ICESat-2 is our only validation. For instance, systematic errors present in ICESat-2 measurements could potentially have been learned by the neural network and propagated across the output dataset. Further, while we use all available and applicable ICESat 2 measurements to assess the DEMs, a small fraction (under 20%) of them was also used to train the CNN model, potentially skewing the results. Finally, since our results above (Figures 4 and 5) suggest that ICESat-2 itself contains significant error in densely-populated areas, we seek further validation to better understand CoastalDEM v2.1's performance in such regions. To resolve these concerns, we use two high-accuracy elevation DEMs derived from airborne lidar as ground truth in the error assessments.

In the United States, NOAA makes publicly available high-quality DEMs across the entire US coastline, which are classified to bare earth elevation, with vertical errors <20 cm RMSE [24]. These data are released at about 5 m horizontal resolution, which we downsample to 1 arc-second (about 30 m) using median filtering. Meanwhile, in Australia, Geospace Australia [25] collected and publicly released bare-earth lidar-derived elevation data along much of their coastlines. These data offer <16 cm vertical RMSE [26] at roughly 25 m horizontal resolution, which we also downsample to 1-arcsecond to match CoastalDEM v2.1.

National results for both the US and Australia are presented in Table 2. We focus on grid cells with population densities exceeding 1,000 per square kilometer. We can again see that CoastalDEM v2.1 exhibits median bias substantially closer to zero than each competing global DEM, and lower RMSE/LE90 values in the elevation band <5 m. CoastalDEM v2.1 even outperforms CoastalDEM v1.1 in the US, which is particularly notable, as the latter was specifically trained using NOAA's lidar-based US coastal DEMs as ground truth.

Figure 6 presents error maps in select cities in the US and Australia. Colors represent the difference between elevation according to the designed global DEM and the corresponding lidar-derived DEM. We can see how CoastalDEM v2.1 performs strongly relative to the other DEMs overall. Of special note is the region around Miami, FL – possibly due to dense development and vegetation, multi-meter biases are present in all past global DEM's across most of south Florida. CoastalDEM v2.1 is the first to have brought down and flattened errors here, without appearing to compromise accuracy in other areas of the US.

Finally, US state-level choropleths of median bias and RMSE for each global DEM can be found in Figures 7 and 8. Again considering points below 5 m and with >1,000 people per square kilometer, we find that CoastalDEM v2.1 median bias outperforms the competing global DEMs in all but three states (Maine, Rhode Island, and Pennsylvania).

These error statistics derived from DEMs based on airborne lidar are overall similar to the global results using data based on ICESat-2 satellite lidar. The airborne lidar ground-truth values were not used in computing CoastalDEM v2.1. The consistency in error assessment across testing approaches mitigates concerns about potential overfitting of our neural network model.

Table 2. Error statistics in the USA and Australia across each DEM and three elevation thresholds (5 m, 10 m, and 20 m). Airborne lidar-derived elevation data are used as ground truth. For each row, only pixels are included whose elevation falls below the elevation threshold (according to ground truth or the DEM), and whose population density exceeds 1K per square kilometer. Rows presenting CoastalDEM v2.1 statistics are in bold. All units are in meters

Nation	DEM	Max Elev	Mean	Median	RMSE	LE90
USA	**CoastalDEM v2.1**	**5**	**-0.12**	**-0.06**	**1.95**	**2.83**
USA	CoastalDEM v1.1	5	0.47	0.59	2.42	3.30
USA	NASADEM	5	1.89	1.66	3.60	5.49
USA	TanDEM-X	5	2.38	1.91	3.36	4.79
USA	MERIT	5	3.19	3.11	3.97	5.72
USA	AW3D30	5	3.65	3.54	5.06	6.94
USA	**CoastalDEM v2.1**	**10**	**-0.27**	**-0.20**	**2.11**	**3.09**
USA	CoastalDEM v1.1	10	0.16	0.23	2.58	3.50
USA	NASADEM	10	1.99	1.72	3.63	5.59
USA	TanDEM-X	10	2.49	1.98	3.49	5.02
USA	MERIT	10	2.90	2.82	3.71	5.35
USA	AW3D30	10	3.45	3.23	4.85	6.69
USA	**CoastalDEM v2.1**	**20**	**-0.36**	**-0.24**	**2.36**	**3.43**
USA	CoastalDEM v1.1	20	0.72	0.38	3.37	4.95
USA	NASADEM	20	2.02	1.72	3.71	5.68
USA	TanDEM-X	20	2.66	2.09	3.75	5.40
USA	MERIT	20	2.74	2.65	3.67	5.26
USA	AW3D30	20	3.36	3.14	4.87	6.70
Australia	**CoastalDEM v2.1**	**5**	**-0.23**	**0.10**	**2.49**	**3.63**
Australia	CoastalDEM v1.1	5	-0.24	-0.19	2.33	3.33
Australia	NASADEM	5	1.53	1.23	3.54	5.41
Australia	TanDEM-X	5	2.01	1.50	2.99	4.26
Australia	MERIT	5	2.51	2.43	3.98	5.54
Australia	AW3D30	5	2.97	2.67	4.06	5.43
Australia	**CoastalDEM v2.1**	**10**	**-0.75**	**-0.34**	**3.00**	**4.53**
Australia	CoastalDEM v1.1	10	-0.29	-0.35	2.71	3.71
Australia	NASADEM	10	1.80	1.51	3.67	5.54
Australia	TanDEM-X	10	1.98	1.46	2.99	4.25
Australia	MERIT	10	2.57	2.45	4.11	5.74
Australia	AW3D30	10	3.10	2.79	4.15	5.41
Australia	**CoastalDEM v2.1**	**20**	**-0.97**	**-0.51**	**3.55**	**5.29**
Australia	CoastalDEM v1.1	20	0.66	0.17	3.43	5.13
Australia	NASADEM	20	1.94	1.63	3.73	5.69
Australia	TanDEM-X	20	2.01	1.50	3.06	4.41
Australia	MERIT	20	2.62	2.50	4.31	6.15
Australia	AW3D30	20	3.24	2.97	4.22	5.51

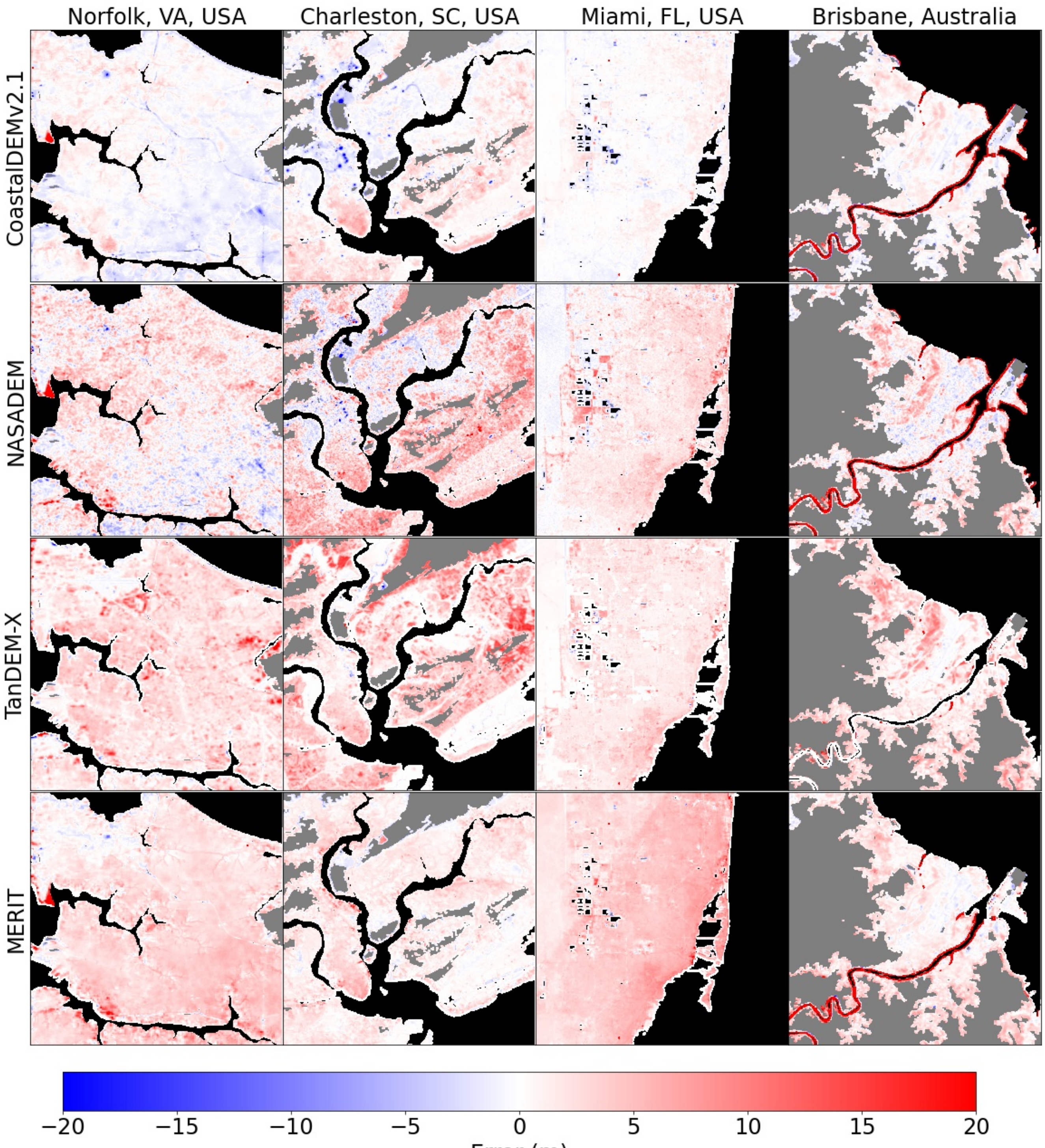

Figure 6. Maps of select US and Australian cities presenting the difference between global DEMs (CoastalDEM v2.1, NASADEM, TanDEM-X, and MERIT) and a lidar-derived DEM. Black areas represent existing water bodies, and gray areas represent pixels whose elevation exceeds 20m.

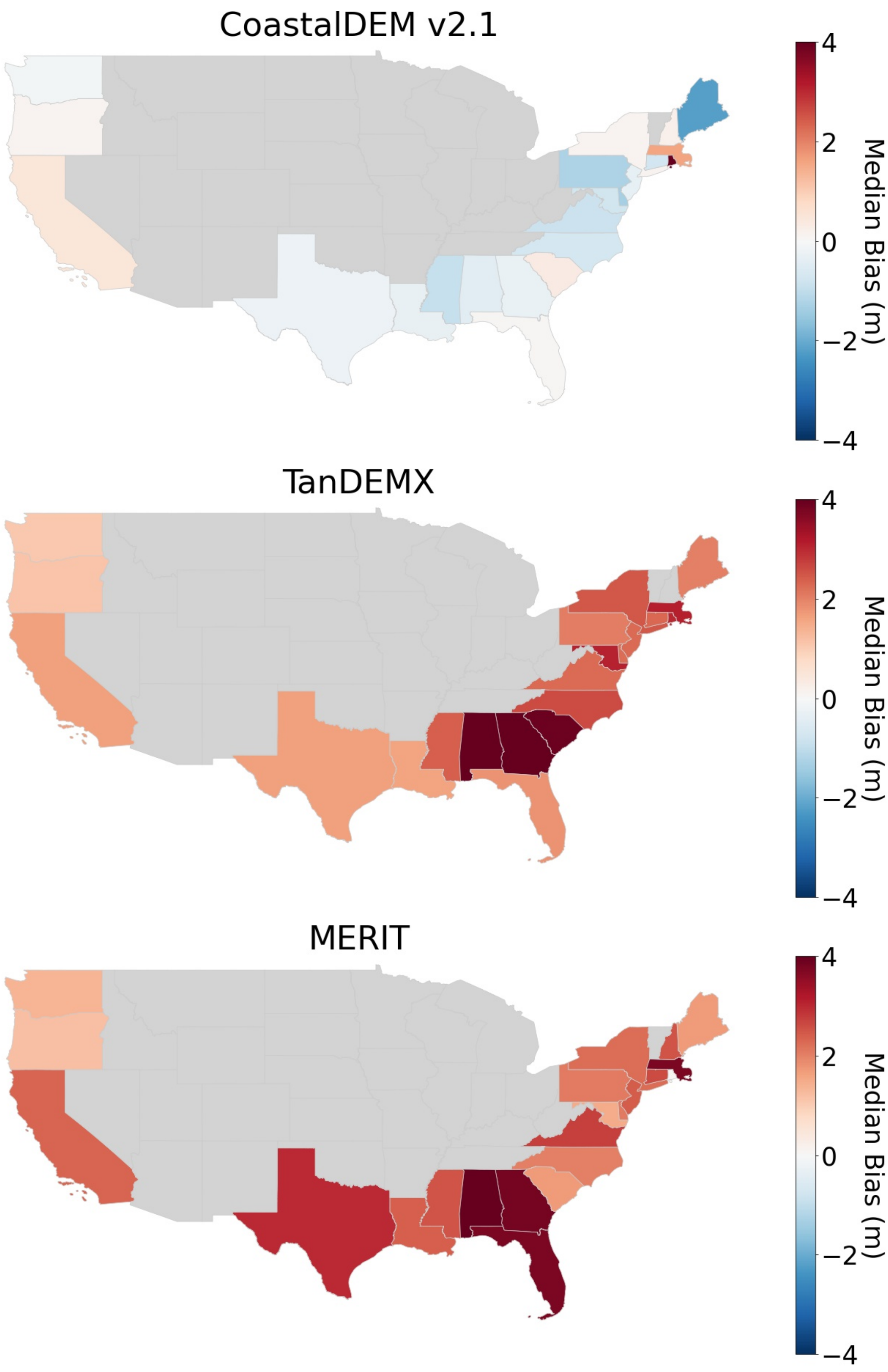

Figure 7. Choropleths presenting median bias under CoastalDEM v2.1, NASADEM, TanDEM-X, and MERIT in low-elevation regions across US states, using elevation data from NOAA's coastal lidar as ground truth. Only pixels whose elevations are lower than 5 m are considered. Only areas with population densities above 1,000 people per square kilometer are included.

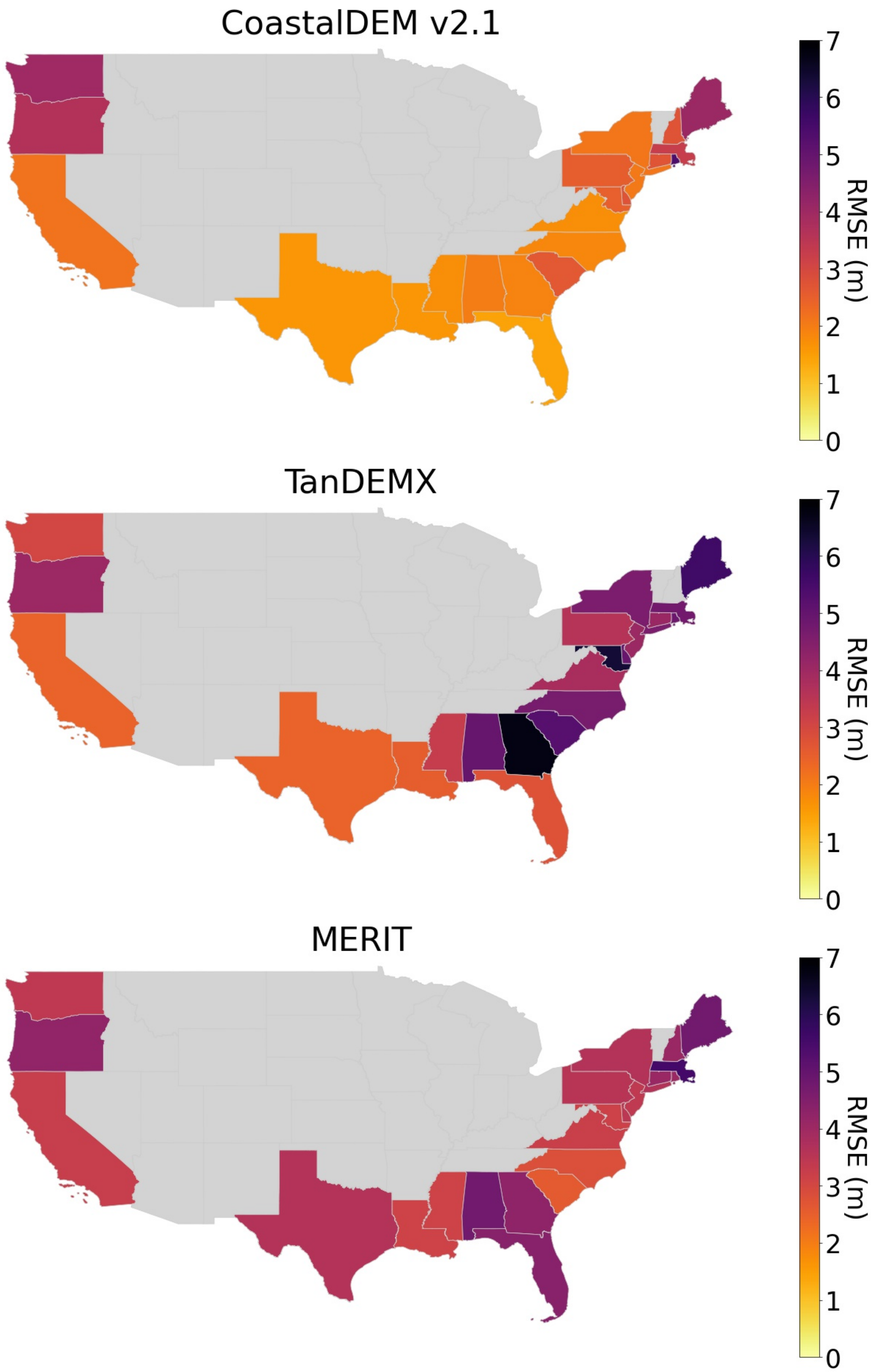

Figure 8. Choropleths presenting median RMSE under CoastalDEM v2.1, NASADEM, TanDEM-X, and MERIT in low-elevation regions across US states, using elevation data from NOAA's coastal lidar as ground truth. Only pixels whose elevations are lower than 5 m are considered. Only areas with population densities above 1,000 people per square kilometer are included.

4. Discussion

Climate Central has invested and will continue to invest significant resources and energy into improving CoastalDEM. As more and improved additional data sets become available, we intend to add them in improving the neural network.

As proud of CoastalDEM performance as we are, we acknowledge that neither CoastalDEM nor any global product is likely to ever outperform high-quality airborne lidar elevation data. While acknowledging the high current cost of comprehensive airborne lidar data collection, we strongly encourage coastal countries and allied entities to develop and freely release quality airborne lidar data for use in evaluating coastal flood risk – and in so doing, retire the need for higher-error global datasets like CoastalDEM.

We also acknowledge that the original SRTM data from which NASADEM and CoastalDEM were derived was collected in year 2000. The surface of the earth is changing with time, especially in areas prone to subsidence due to high rates of groundwater or fossil fuel extraction, or river-delta-sediment compaction. In addition, artificial earth works have the potential to alter the coastal risk profiles represented by SRTM, NASADEM, and CoastalDEM. This temporal quality calls for more up-to-date and regular refreshes of coastal DEMs with airborne lidar and new remote sensing capabilities that may become available.

5. Conclusion

CoastalDEM was developed to provide an improved, widely available, near-global digital elevation model for the primary purpose of evaluating coastal flood risk considering storms and sea level rise. With this use case in mind, elevations below 5 m are of particular interest as they span the range of most tides, storms, and projected sea-level-rise scenarios through the year 2100.

In addition, coastal areas with high population density are both areas where accurate vulnerability assessments are especially important and areas where the urbanized, built environment has challenged remote sensing technologies intended to measure ground elevations, resulting in material vertical bias that negatively impacts coastal flood risk assessments. Reducing vertical bias was the primary objective of creating CoastalDEM v1.1 and the objective of investing in the improvements with CoastalDEM v2.1. Reducing error scatter, measured by RMSE and LE90, was the secondary objective.

Performance data indicate vertical bias and error scatter are consistently and substantially reduced with CoastalDEM v2.1. With version 2.1, CoastalDEM further improves its reduced-bias performance lead over comparable global DEMs. CoastalDEM v2.1 is particularly strong in the elevation range below 5 m where coastal flood risk is acute and in densely populated regions where buildings and the built environment adversely affect other global DEMs. Near-zero bias means smaller elevation errors propagating into coastal flood analysis so critical to understanding the threat posed by sea level rise.

6. Availability

CoastalDEM v2.1 is available at 30 m and 90-m horizontal resolution by license from Climate Central via `https://go.climatecentral.org/coastaldem/`. No-cost, non-commercial licenses at 90 m horizontal resolution are available to qualified academic and research organizations (see Supplementary Dataset 2 for 90 m error statistics). With no-cost licenses available and vertical bias demonstrably near zero, CoastalDEM v2.1 is a superior global DEM for sea level rise and coastal flood risk assessments.

7. Methods

7.1 ICESat-2

NASA distributes ICESat-2 measurements as a large collection of HDF5 files. Here, we download the entirety of the L3A Land and Vegetation Height Version 3 (ATL08) dataset [27], which contains a number of elevation metrics at points 12 m apart along six beam tracks. For each point, we extract the fields *h_te_mean*, *latitude*, *longitude*, and *layer_flag*. The variable *h_te_mean* refers to the mean height returned by photons within the point's footprint, and *layer_flag* is a binary variable that is 1 if the point is likely covered by snow or clouds (points flagged as such are removed). Elevations are referenced to WGS84, which we convert to EGM96 using NOAA's VDatum tool [28]. All points in the entire ICESat-2 dataset meeting the given requirements and filters described in this report were used in the assessments.

7.2 CoastalDEM v2.1

Like CoastalDEM v1.1, CoastalDEM v2.1 uses an artificial neural network to predict errors present in another global DEM (here, NASADEM), using a number of global datasets as inputs. These inputs include elevation, population density, and vegetation density and height metrics. In total, CoastalDEM v2.1 ingests 7 independent input datasets to feed the model.

Instead of using a multilayer perceptron network as with CoastalDEM v1.1, CoastalDEM v2.1 employs a larger and more sophisticated convolutional neural network architecture [29]. CNNs are specifically designed for and are widely used in tasks involving imagery, making them a good fit for the raster datasets used here.

Where CoastalDEM v1.1 was trained using airborne lidar-derived elevation data as ground truth, in the US only, CoastalDEM v2.1 was instead trained using global ICESat-2 elevation measurements. While these data are not as accurate as airborne lidar, using such a global dataset reduces the risk of overfitting the model on US-centric data. Further, while CoastalDEM v1.1 was trained and defined only where SRTM elevations were between 1 and 20 m, CoastalDEM v2.1 is generated where NASADEM elevations are between -10 and 120 m, capturing a much larger domain.

Acknowledgments

The authors gratefully acknowledge Don Bain and Kelly Van Baalen for their thoughtful insights and comments on the manuscript. This research was supported by Climate Central and grants from the National Science Foundation (ICER-1663807) and the National Aeronautics and Space Administration (80NSSC17K0698).

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