Reviewer Comments
Author Response
Proposed Text Changes

Anonymous Referee #1

Received and published: 7 January 2019

Very well written paper with clear conclusions. However, in some places the text is a bit terse/too condensed for a relative non-expert on this type of modelling to follow. A suggestion is to expand on some of the sentences a bit, esp. where I put comments. Minor comments are attached. Please also note the supplement to this comment: https://www.earth-surf-dynam-discuss.net/esurf-2018-79/esurf-2018-79-RC1- supplement.pdf

Page 2, line 9: Why elevation and not the constituency of the substrate?

We have added detail to the sentence to reflect the fact that substrate, underlying geology, and other processes determine coastal elevation, which can then be used as an important parameter in determining land cover distribution. We have modified the manuscript text as follows:

Page 1, Line 33: Because coastal land elevation is primarily governed by the substrate and/or underlying geology of the landscape as well as a product of the physical and biogeochemical processes acting on it, it serves as a central parameter in defining the distribution and configuration of ecosystems and their ability to evolve in response to processes driving change (Gesch, 2009; Kempeneers et al., 2009).

Page 2, line 20: Just "model skill"

We have revised the text from "skillfulness" to "skill" as suggested.

Page 2, line 26: Reduces?

We have replaced "refines" with "reduces" as suggested.

Page 2, line 27: Don't understand this part of the sentence. If the error in these datasets has negligible impact on outcomes, why bother to look at them?

The intent of this part of the sentence was to state that a secondary component of our hypothesis is that process uncertainty can play a much greater role in our model outcomes than data error, and we test this by determining whether data improvements will have a measurable impact on model outcomes. In other words, if data improvements do not substantially change our predicted outcomes, we are able to demonstrate process uncertainty plays a greater role than data error in our predictions, and conversely, we can point out that data errors can be important if they obscure an important process threshold. To reduce confusion, have revised the sentence as follows to clarify our intent:

Page 2, Line 16: We hypothesize that the relationship between these data inputs over such an extensive and diverse expanse reduces uncertainty in each parameter in our framework, and that that potential data error is sufficiently minor that it does not obscure important process thresholds that would in turn affect predicted outcomes.

Page 5, line 27: This goes too fast—where and how should I read the graphs to conclude this?

We have added detail to the sentence to break this down a bit, referencing specific parts of the figure throughout the sentence so that this is more easily digestible for the reader. Please note our revisions correspond to the revised version of the figure and have been submitted as part of the revised manuscript.

Page 5, Line 17: Figure 1a shows that when E data were used to predict LC, subaqueous environments were the most probable prediction for elevations lower than 0 m (as illustrated by the first four plots on the left).

Page 5, line 28: OK on subaqueous, but I don't understand why marsh is predicted for elevations between 5-10 meters.

Both R1 and R2 have found this inconsistency in our plotted data. We originally attributed this to elevation inaccuracies associated with vegetation in the marshes and alluded to this as such in the discussion. However, these technical observations warranted a review of the original training dataset, wherein we found a minor data truncation issue that caused marshes in this elevation range to be disproportionately represented as compared with others. We have rectified this issue and have remade corresponding tables (Supplemental Tables 3 and 4) and Figure 1 to demonstrate that the impacts of the truncation were relatively minor and have not substantially changed our results, interpretations of these results, or conclusions. We have included corrected tables and a revised Figure 1 and have made minor corrections to the corresponding areas in the manuscript that cites these numbers in resubmission. Specifically:

Page 5, Line 27: When relying on the original prior LC distribution, the network had a corresponding accuracy rate of 69%, and found beaches and rocky areas as more probable than another land cover type. Here, beaches were most commonly confused with subaqueous and marsh land cover types, and rocky areas with subaqueous (Table S3a). Uniformly distributed LC priors yielded slightly different predicted outcomes, wherein the network never found rocky and forested land cover types more probable than another land cover type, most commonly confusing them with subaqueous and developed land cover types respectively (Table S3b). Overall, the accuracy rate in the inference relationship between E and LC was 56% when uniform LC prior distributions were used (Table 1).

and

Page 6, Line 1: The difference in prediction using the uniform-prior BN was that the 5-10 m range category was predicted, whereas this elevation was not more probable than another when original priors were used. The accuracy rate in the inference relationship between LC and E was 66% for the original prior distribution and 58% for the uniform priors (Table 1).

and

Page 7, Line 14: Assessing model skill in the E and LC relationship revealed an accuracy of 56% (uniform priors) to 69% (non-uniform priors), showing that including the regional LC bias helped to improve predictions (Table 1), and that the most commonly missed LC-E predictions occurred in elevations closest to mean sea level (-1 to 1 m).

Page 6, line 5: Where do I see that number in the tables?

The accuracy rate was available in the accompanying table captions for the confusion matrices. To make accuracy rates easier to find, have included a new table that summarizes all accuracy rates. The new table (Table 1) included here and has been included as part of the revised manuscript.

Table 1. Summary table of accuracy rates for all confusion matrices of land cover and elevation comparisons. Accuracy rates are calculated by summing where predictions matched observations (the diagonal bolded terms in Tables S2-S4) and dividing by the total number of outcomes. Confusion matrices are available in supplemental materials (Tables S2-S4).

Confusion Matrix	Accuracy Rate
C-CAP vs. DSL Land Cover comparison	85%
Predicted vs. Observed Land Cover *Elevation inputs; original distributions*	77%
Predicted vs. Observed Land Cover *Elevation inputs; uniform distributions*	65.5%
Predicted vs. Observed Elevation *Land Cover inputs; original distributions*	66%
Predicted vs. Observed Elevation *Land cover inputs; uniform distributions*	59%

Page 6, line 8: Can you comment on why there are no predictions for beach, rocky and developed?

When elevation is used to predict land cover, there are no predictions for beach and rocky in our BN with non-uniform priors (see attached; this is updated based on the truncation issue reported earlier), and no predictions for rocky and forest categories in our uniform BN. In each case, these land cover categories had lower probabilities of occurring in any of specified elevation ranges with respect to another, therefore the BN consistently picked the land cover category that was most probable to occur with the elevation range selected. In other words, the BN certainly makes probabilistic predictions of these land cover categories, but, possibly due to binning (elevation bin ranges are wide), an elevation signature specific to these land cover categories is never found to be the most likely outcome. A similar result can be seen when land cover data are used to predict elevation; under non-uniform land cover priors, the 5 to 10 m range is never predicted because it has such a low probability of occurrence with respect to other ranges.

The difference between the uniform and non-uniform results is due to the under-representation of certain land cover classes regionally. For example, when non-uniform elevation priors are applied, beaches and rocky areas are most infrequent (Figure S1), and because other land cover types areas have a greater representation among all elevation ranges than these land cover types (Figure 1), it appears the model selects the (slightly) more regionally probable land cover class to occur. Conversely, when uniform elevation priors are applied, the model identifies the (slightly) stronger relationship of the 1- 5 m elevation range and developed areas (rather than forests) and given that either land cover class in this *scenario is equally likely, selects land cover based on the most probable (strongest) relationship with elevation.*

In response to the reviewer's question, we have included mention of this lack of prediction of certain land cover types and the reasons behind it in the revised manuscript to enhance our discussion. Our changes include:

Page 7, Line 19: In addition to missed predictions, in certain cases predictions were consistently never the most probable outcome than another for a few land cover types (specifically beaches and rocky under original E priors; rocky and forest under uniform priors (Tables S3) or elevation ranges (5-10 m elevations under original LC priors Table S4b). For the original priors, this is due to the underrepresentation of certain classes (regional bias) in our training data, wherein beaches, rocky, and 5-10 m elevation ranges were infrequent when compared to other classes/bins. In the case of uniform priors, our BN is detecting the slightly stronger relationship of some land cover types certain elevation ranges (e.g. developed in the 1 to 5 m range), thereby making other E-LC relationships never more probable than these. Although bin reassignments that span smaller elevation ranges could help resolve more specific land cover signatures in our model, particularly for low-lying beaches and marshes, this would likely occur at the cost of increased prediction uncertainty as outcomes would span a larger number of bins.

Page 7, line 28: How does tidal stage at which the lidar was flown affect the results for beaches?

All elevation data included in our model were vertically adjusted to mean high water (MHW) from the North American Vertical Datum of 1988. This is a detail that was included in previous work, and that considering this comment, is also important to include in this paper. We have added text to the Data and Methods section to clarify this adjustment. Specifically:

Page 3, Line 4: AE predictions were generated through implementation of a deterministic equation (see Figure S1). First, SLR scenarios were combined with vertical land movement rates due to subsidence and other non-tectonic effects (using rates derived from a combination of GPS CORS stations in Sella et al., 2007; and long-term tide gauge data in Zervas et al., 2013) to make projections relative (local). Projected relative SLR values were then subtracted from elevation data, which were comprised of a combination of high-resolution elevation data from the National Elevation Dataset (NED, Gesch, 2007) supplemented where necessary with coarser resolution bathymetry from the National Oceanic and Atmospheric Administration National Geophysical Data Center's Coastal Relief Model (National Oceanic and Atmospheric Administration, 2014) to predict adjusted land elevation (AE) relative to the projected sea level. Before model integration, high resolution elevation data were converted to mean high water from North American Vertical Datum 1988 using VDatum conversion grids (National Ocean Service, 2012).

Our intent in converting these data was to ensure that tidal impacts on our results were minimized; herein beaches submerged at high tide should still appear as beach in our model, albeit below 0 m. As Figure 1b shows, the most likely E category when beach is predicted is -1 to 0 m; conversely, when the -1 to 0 m range is selected in Figure 1a, we see beach is the most probable category when uniform priors (i.e. the regional bias) is removed. Therefore, to the reviewer's point, it does appear that a submerged tidal stage may have some influence on our results, such that beaches in our model are frequently found to be submerged. We have added detail to the discussion section to reflect this insight including:

Page 7, Line 4: However, beaches are more confidently predicted in the -1 to 0 m range than other land cover types (Figure 1b), suggesting a propensity of beaches in our model training data are shallowly submerged. Using first-return lidar instead of bare earth data in our model could be used to further distinguish the six LC types from one another via vegetation differences (e.g. Lee and Shan, 2003; Im et al., 2008; Reif et al., 2011) and better distinguish intertidal areas, which may allow refinement of marsh, beach, and forest classifications (e.g. Kepeneers et al., 2009; Sturdivant et al., 2017).

and

Page 7, Line 33: Results instead may suggest high-resolution (1/9 NED) E data captures a systematic offset in part due to MHW submergence from datum conversion (Lentz et al., 2015), particularly for marshes and beaches (Fig 3b). In addition to elevation data that accounts for vegetation, as suggested earlier, seamless and continuous topographic and bathymetric data (Danielson et al., 2016) would constrain resolution error and better resolve distinctions between subaerial and subaqueous environments.

Anonymous Referee #2 Received and published: 25 January 2019

This manuscript presents a study of the skill and sensitivity of a model that predicts likelihood of response of low-lying areas to sea level rise. The researchers determine that data errors are most often found in areas of low elevation, but that seems to have little influence on the model's skill due to correlations between land cover and elevation, the two data sets used as inputs to the model. In addition, model sensitivity appears to mimic uncertainty in process, which waves a flag for improving process-based models. The topic of this manuscript is of relevance to researchers in coastal science, applied coastal engineering, and those studying societal impacts of climate change. The manuscript is well-organized, but lacks critical details about how the model works, making the results border on irreproducible. This can be substantially improved by adding a paragraph that provides explicit details of how the model uses the elevation and land cover data sets to compute likelihood of dynamic response. It appears that the Lentz et al. (2016) paper may provide more information about the model itself. If that is the case, I can appreciate that the authors chose not to be redundant by reiterating all of that information, but I, myself, found it difficult to read this paper as a standalone contribution. I acknowledge that researchers working on similar projects will likely have read the Lentz et al. (2016) paper, thereby making this manuscript more understandable.

This paper could be improved by some more detailed explanations and examples, particularly the Data and Methods section. Also, it would be helpful if the 'nuts and bolts' of the modeling were summarized, even if not fully detailed as I assume they are in the previous publications. If these improvements can be implemented, I would be happy to recommend this paper for publication, provided the specific comments below are considered and addressed as well.

We have included more detail regarding how the model works in a revised submission. Our comments to follow detail how we have incorporated more specific information in our revision. In addition to these changes, we have revisited the entire manuscript to ensure that pertinent details important for the reader are available in the text, so it can be read as a standalone contribution. We have revised the Previous Work section in Data and Methods to provide detail as suggested including the following:

Page 2, Line 22:

2.1 Previous Work

Lentz et al. (2015) mapped coastal response predictions—the probability of dynamic response or DP—using a Bayesian network (BN) probabilistic modelling approach. We define DP as the likelihood of land cover type to retain its existing state or transition to a new non-submerged state under the given SLR projection. By this definition, coastal response is a binary outcome, in that if the coast does not respond dynamically to SLR, it will inundate, therefore DP equals one minus the probability of inundation. A DP value of 0.5 indicated highest uncertainty in that either dynamic response or inundation had an equally likely probability of occurrence (Lentz et al., 2016).

The study area was a 38,000 km^2 region from Maine to Virginia, U.S.A., bounded by the 10-m elevation contour inland to -10 m offshore. The BN (Figure S1) produced two probabilistic outcomes at a 30 x 30 m resolution for future SLR scenarios in the 2020s, 2030s, 2050s, and 2080s: 1) adjusted land elevation (AE) relative to the projected sea level, and 2) dynamic response or DP. As described in Lentz et al. (2015), the SLR scenarios were comprised of three components: ocean dynamics (generated from 24 Coupled Model Intercomparison Project Phase 5 (CMIP5 models (Taylor et al., 2015), ice melt (as estimated by Bamber and Aspinall, 2013 for the two Antarctic Ice Sheets, and glaciers and ice caps as based on Marzion et al, 2012 and Radic et al., 2013), and global land water storage (as based on Church et al., 2013). Percentiles of these three components were estimated and then aggregated to provide a SLR scenario and corresponding uncertainty. The projected SLR scenario ranges for each decade used in our model are shown in Figure S1 as follows: 2020s (0 to 0.25 m); 2030s (0.25 to 0.5 m); 2050s (0.5 to 0.75 m) and 2080s (0.75 to 2 m).

AE predictions were generated through implementation of a deterministic equation (see Figure S1). First, SLR scenarios were combined with vertical land movement rates due to subsidence and other non-tectonic effects (using rates derived from a combination of GPS CORS stations in Sella et al., 2007; and long-term tide gauge data in Zervas et al., 2013) to make projections relative (local). Projected relative SLR values were then subtracted from elevation data, which were comprised of a combination of high-resolution elevation data from the National Elevation Dataset (NED, Gesch, 2007) supplemented where necessary with coarser resolution bathymetry from the National Oceanic and Atmospheric Administration National Geophysical Data Center's Coastal Relief Model (National Oceanic and Atmospheric Administration, 2014) to predict adjusted land elevation (AE) relative to the projected sea level. Before model integration, high resolution elevation data were converted to mean high water from North American Vertical Datum 1988 using VDatum conversion grids (National Ocean Service, 2012).

Dynamic response probabilities (DP) were estimated by coupling the predicted AE ranges with expert knowledge on the response of generalized land cover types (six categories that respond distinctly to SLR ecologically or morphologically--subaqueous, marsh, beach, rocky, forest, and developed--as described in Lentz et al. (2015) and shown in Table S1). Although the resulting predictions provided a robust accounting of uncertainty from some of the data inputs and knowledge of physical landscape change processes, the relative influence of these uncertainties on the predictions has not been explored explicitly.

Specific Comments:

Page 2, Line 3: "across increasing slopes" is confusing here – do the authors imply that as one moves landward from the shoreline, the topographic slope (dz/dx) increases necessarily? That is not the case.

We agree that topographic slope does not necessary increase from the shoreline and we have removed "across increasing slopes" from the sentence.

Page 2, Line 4: "a relatively stable SLR rate"– do the authors mean "a relatively steady SLR rate", meaning there has been little acceleration over the last few thousand years? Or do they mean that sea level reached its current elevation a few thousand years ago and has only begun rising again in the last few centuries (likely due to anthropogenic influence)? The word "stable" is misleading (to me, at least).

We agree that "steady" is a better word choice than "stable" in this sentence given the concerns the reviewer has outlined; this change has been incorporated.

Figures – much of the labeling is done in font so small that they are barely readable. Even changing the magnification on the computer screen results in pixilation. This aesthetic shortcoming undermines the value of the figures.

The labeling in both the figures has been enlarged so that font is easily readable; we have also revised Figure 1 considering comments from R1, as well as to improve both readability and aesthetics. The revised Figure 1 is in the revised manuscript.

Page 2, Line 19: "The confidence of our probabilistic SLR predictions depends on. . . land cover and elevation data." This doesn't seem correct. It's not SLR predictions themselves that depend on these inputs, but rather the inundation patterns resulting from SLR estimates that depend on LC and Elev., right?

This is correct; we have replaced "probabilistic SLR predictions" with "probabilistic dynamic response *outcomes" for clarity.*

Page 2, Line 31: It is unclear what is meant by "coastal response outcomes".

The term "coastal response outcome" has been reworked to be more specifically defined to the overall probability of dynamic response. Specifically:

Page 2, Line 23: Lentz et al. (2015) mapped coastal response predictions—the probability of dynamic response or DP—using a Bayesian network (BN) probabilistic modelling approach. We define DP as the likelihood of land cover type to retain its existing state or transition to a new non-submerged state under the given SLR projection. By this definition, coastal response is a binary outcome, in that if the coast does not respond dynamically to SLR, it will inundate, therefore DP equals one minus the probability of inundation. A DP value of 0.5 indicated highest uncertainty in that either dynamic response or inundation had an equally likely probability of occurrence (Lentz et al., 2016).

I see that on the first line of Page 3, the authors say that the "BN produced two outcomes. . ." for four different decades. Two outcomes of what? And for those decades, I assume the authors are implying that there are projected sea level elevations during those decades – what are they?

The two outcomes are adjusted land elevation with respect to projected sea-level rise and dynamic response probabilities. The projected sea level elevations are themselves probabilistic based on the decade for which they are predicted. The ranges for these projections are shown in Figure S1. We have modified the text to provide more specificity regarding these ranges and their time correspondence. Specifically:

Page 2, Line 31: The BN (Figure S1) produced two probabilistic outcomes at a 30 x 30 m resolution for future SLR scenarios in the 2020s, 2030s, 2050s, and 2080s: 1) adjusted land elevation (AE) relative to the projected sea level, and 2) dynamic response or DP. As described in Lentz et al. (2015), the SLR scenarios were comprised of three components: ocean dynamics (generated from 24 Coupled Model Intercomparison Project Phase 5 (CMIP5 models (Taylor et al., 2015), ice melt (as estimated by Bamber and Aspinall, 2013 for the two Antarctic Ice Sheets, and glaciers and ice caps as based on Marzion et al, 2012 and Radic et al., 2013)), and global land water storage (as based on Church et al., 2013). Percentiles of these three components were estimated and then aggregated to provide a SLR scenario and corresponding uncertainty. The projected SLR scenario ranges for each decade used in our model are shown in Figure S1 as follows: 2020s (0 to 0.25 m); 2030s (0.25 to 0.5 m); 2050s (0.5 to 0.75 m) and 2080s (0.75 to 2 m).

Bamber, J.L., and Aspinall, W.P.: An expert judgment assessment of future sea-level rise from the ice sheets: *Nat. Clim. Change* 3(4), 424–427, 2013.
Marzion, B., Jarosch, A.H., and Hofer, M.: Past and future sea-level change from the surface mass balance of glaciers: *The Cryosphere*, 6(6), 1295–1322, 2012.
Radić, V., Bliss, A., Beedlow, C.D., Hock, R., Miles, E., and Cogley, J.G.: Regional and global projections of twenty-first century glacier mass changes in response to climate scenarios from global climate models: *Climate Dynam.* 42 (1–2), 37–58, 2013.
Taylor, K.E., Stouffer, R.J., and Meehl, G.A.: An overview of CMIP5 and the experiment design: *B. Am. Math. Soc.*, 93(4), p. 485–498, 2012.

As I read on, I see that the authors refer to the equation in the supplemental material, Figure S1, which tells us that adjusted elevation is present elevation minus sea level rise plus vertical land motion (VLM). How is VLM obtained?

VLM was obtained by coupling GPS CORS station data (Sella et al., 2009) with long term tide gauge data (Zervas et al., 2013). These point data were used to create an interpolated VLM surface, from which VLM rates were extracted at all point locations. We have included these details and references to the citations below to provide the reader this context in a revised submission. Specifically:

Page 3, Line 4: AE predictions were generated through implementation of a deterministic equation (see Figure S1). First, SLR scenarios were combined with vertical land movement rates due to subsidence and other non-tectonic effects (using rates derived from a combination of GPS CORS stations in Sella et al., 2007; and long-term tide gauge data in Zervas et al., 2013) to make projections relative (local).

Sella, G.F., Stein, Seth, Dixon, T.H., Craymer, Michael, James, T.S., Mazzotti, Stephane, and Dokka, R.K., 2007, Observation of glacial isostatic adjustment in “stable” North America with GPS: Geophysical Research Letters, v. 34, no. 2, L02306, 6 p., http://dx.doi.org/10.1029/2006GL027081, GPS Data
Zervas, Chris, Gill, Stephen, and Sweet, William, 2013, Estimating Vertical Land Motion from Long-Term Tide Gauge Records: National Oceanographic and Atmospheric Administration Technical Report NOS CO-OPS 065, 30 p., Long Term Tide Data and Report.

Also in Figure S1, it appears that coastal response can have one of two outcomes: “dynamic” or “inundate”. Is “dynamic” the right term here? Does it imply “non-inundate”?

Coastal response predictions are themselves binary; the reviewer is correct in deducing that “dynamic” can also mean “non-inundate”. Our text on page 2, lines 9-10 is an attempt to make this point as well, *but given reviewer confusion, we have added additional detail the caption to make this point clear. Specifically:*

Page 2, Line 23: Lentz et al. (2015) mapped coastal response predictions—the probability of dynamic response or DP—using a Bayesian network (BN) probabilistic modelling approach. We define DP as the likelihood of land cover type to retain its existing state or transition to a new non-submerged state under the given SLR projection. By this definition, coastal response is a binary outcome, in that if the coast does not respond dynamically to SLR, it will inundate, therefore DP equals one minus the probability of inundation. A DP value of 0.5 indicated highest uncertainty in that either dynamic response or inundation had an equally likely probability of occurrence (Lentz et al., 2016).

and

Caption for Figure S1: Diagram showing Bayesian network coastal response model, including data inputs (left) and predicted outcomes (right), including adjusted elevation (inundation model equivalent) and coastal response, wherein the response is binary such that dynamic implies “non-inundate”.

Figure 1, Panel A: I don’t understand why the model predicts that everything within the 5-10m elevation bin is predicted to be “Marsh”. That seems to be an inaccurate prediction from the model.

See earlier comments in response to R1 that address this point.

Proposed Figure Revisions and Supplemental Table Revisions:

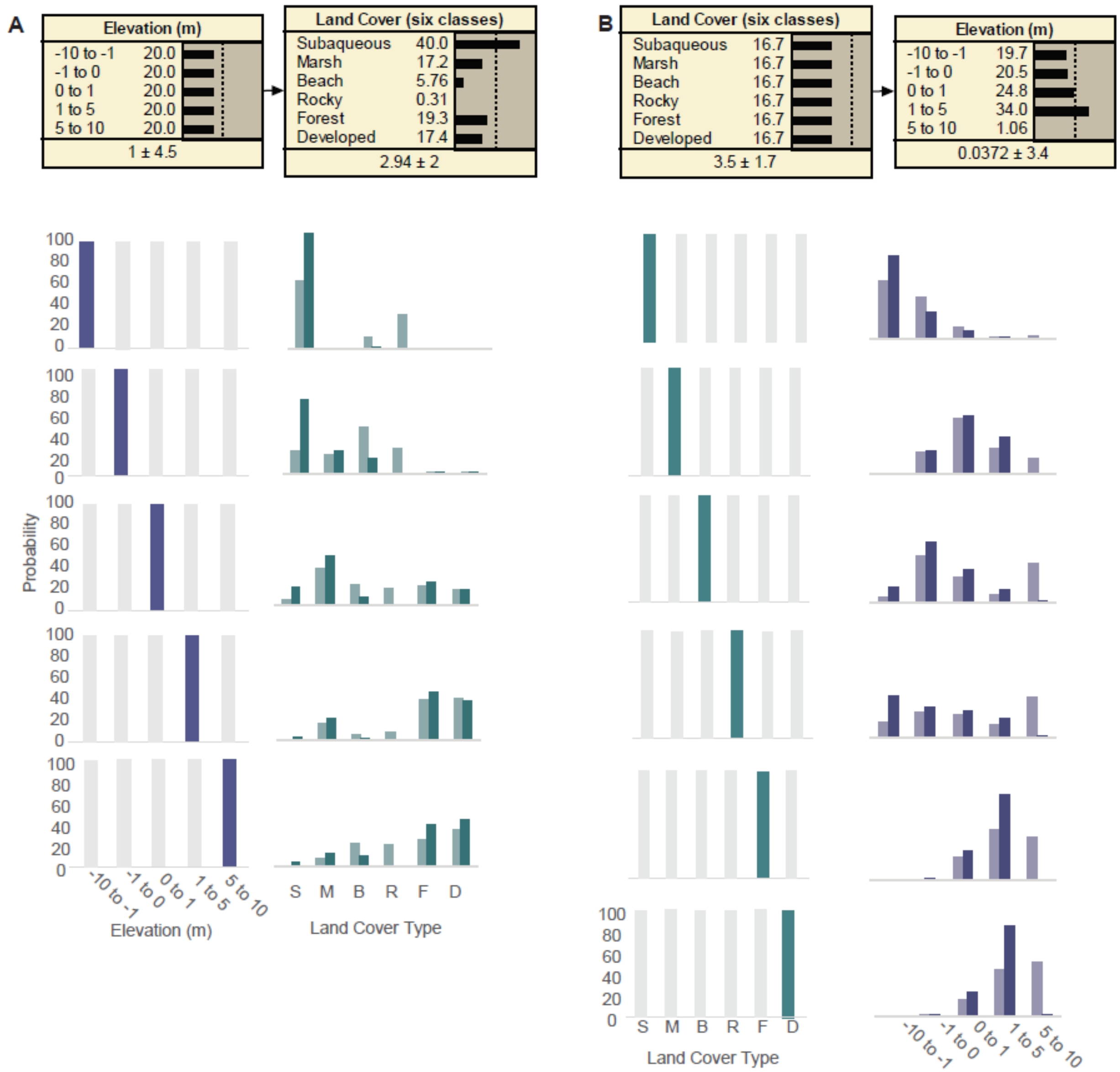

Figure 1. Updated probability distributions after training between elevation and land cover datasets with non-uniform (dark) and uniform (light) priors (the latter to limit regional LC bias), a) showing land cover distributions under selected elevation ranges and b) showing elevation distributions under selected land cover types. Land cover categories (Table S1) abbreviated as follows: S = subaqueous; M = marsh; B = beach; R = rocky; F = forest; and D = developed.

	Predicted (m)							
Actual	**Water**	**Marsh**	**Beach**	**Rocky**	**Forest**	**Developed**	**Total**	**User's accuracy (%)**
Water	**22091861**	1591392	0	0	446390	12107	24141750	91.5
Marsh	1290019	**2918228**	0	0	1890412	25752	6124411	47.6
Beach	1048226	450741	**0**	0	174218	21048	1694233	0
Rocky	62315	22883	0	**0**	15976	1240	102414	0
Forest	147539	1420429	0	0	**4016932**	80731	5665631	70.9
Developed	139712	925392	0	0	3352471	**90485**	4508060	2
Ground truth	24779672	7329065	0	0	9896399	231363	**42236499**	
Producer's accuracy (%)	89.2	39.8			40.6	39.1		

Table S3a. Confusion matrix showing comparison between predicted land cover and measured (observed) land cover when elevation data are used as inputs with original distributions, with user's error (accuracy) and producer's error (reliability). The overall accuracy rate for this comparison is 69%.

	Predicted (m)							
Actual	**Water**	**Marsh**	**Beach**	**Rocky**	**Forest**	**Developed**	**Total**	**User's accuracy (%)**
Water	**16530433**	1591392	5561428	0	0	458497	24141750	68.5
Marsh	60470	**2918228**	1229549	0	0	1916164	6124411	47.6
Beach	217137	450741	**831089**	0	0	195266	1694233	49.1
Rocky	35964	22883	26351	**0**	0	17216	102414	0.0
Forest	11445	1420429	136094	0	**0**	4097663	5665631	0.0
Developed	26099	925392	113613	0	0	**3442956**	4508060	76.4
Ground truth	16881548	7329065	7898124	0	0	10127762	**42236499**	
Producer's accuracy (%)	97.9	39.8	10.5			34		

Table S3b. Confusion matrix showing comparison between predicted land cover and measured (observed) land cover when elevation data are used as inputs with uniform distributions, with user's error (accuracy) and producer's error (reliability). The overall accuracy rate for this comparison is 56%.

Predicted (m)

Actual (m)	**-10 to -1**	**-1 to 0**	**0 to 1**	**1 to 5**	**5 to 10**	**Total**	**User's accuracy (%)**
-10 to -1	**16566397**	217137	60470	37544	0	16881548	98.1
-1 to 0	5587779	**831089**	1229549	249707	0	7898124	10.5
0 to 1	1614275	450741	**2918228**	2345821	0	7329065	39.8
1 to 5	462366	174218	1890412	**7369403**	0	9896399	74.5
5 to 10	13347	21048	25752	171216	**0**	231363	0
Ground truth	24244164	1694233	6124411	10173691	0	**42236499**	
Producer's accuracy (%)	68.3	49.1	47.6	72.4			

Table S4a. Confusion matrix showing comparison between predicted elevations and measured (observed) elevations when land cover data are used as inputs with original distributions, with user's error (accuracy) and producer's error (reliability). The overall accuracy rate for this comparison is 66%.

Predicted (m)

Actual (m)	**-10 to -1**	**-1 to 0**	**0 to 1**	**1 to 5**	**5 to 10**	**Total**	**User's accuracy (%)**
-10 to -1	**16530433**	217137	60470	11445	62063	16881548	97.9
-1 to 0	5561428	**831089**	1229549	136094	139964	7898124	10.5
0 to 1	1591392	450741	**2918228**	1420429	948275	7329065	39.8
1 to 5	446390	174218	1890412	**4016932**	3368447	9896399	40.6
5 to 10	12107	21048	25752	80731	**91725**	231363	39.6
Ground truth	24141750	1694233	6124411	5665631	4610474	**42236499**	
Producer's accuracy (%)	68.5	49.1	20.1	70.9	73.1		

Table S4b. Confusion matrix showing comparison between predicted elevations and measured (observed) elevations when land cover data are used as inputs with uniform distributions, with user's error (accuracy) and producer's error (reliability). The overall accuracy rate for this comparison is 58%.

Relationships between regional coastal land cover distributions and elevation reveal data uncertainty in a sea-level rise impacts model

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Abstract. Understanding land loss or resilience in response to sea-level rise (SLR) requires spatially extensive and continuous datasets to capture landscape variability. We investigate sensitivity and skill of a model that predicts dynamic response likelihood to SLR across the northeastern U.S. by exploring several data inputs and outcomes. Using elevation and land cover datasets, we determine where data error is likely, quantify its effect on predictions, and evaluate its influence on prediction confidence. Results show data error is concentrated in low-lying areas with little impact on prediction skill, as the inherent correlation between the datasets can be exploited to reduce data uncertainty using Bayesian inference. This suggests the approach may be extended to regions with limited data availability and/or poor quality. Furthermore, we verify that model sensitivity in these first-order landscape change assessments is well-matched to larger coastal process uncertainties, for which process-based models are important complements to further reduce uncertainty.

1 Introduction

Estimates of global sea-level rise (SLR) predict increases between 0.3 by 1.2 meters by 2100 (Church et al., 2013; Kopp et al., 2014), while Northeastern and Mid-Atlantic U.S. SLR projections are higher than the global average due to a variety of factors including subsidence, static equilibrium effects and changing ocean dynamics (Goddard et al., 2015; Mitrovica et al., 2011; Kopp, et al., 2014; Sella et al., 2009; Slangen et al., 2014; Sweet et al., 2017a,b; Yin & Goddard, 2013; Yin et al., 2009; Zervas et al., 2013). SLR impacts such as high tide flooding, barrier island narrowing, and salt marsh degradation have been increasingly observed along the U.S. East Coast (e.g. Cahoon et al., 2009; Ezer & Atkinson, 2014; Kirwan & Megonigal, 2013; Sweet & Park, 2014). The northeastern U.S. coast (Figure 1) is a diverse landscape, with major shipping ports, heavily populated cities, and extensive natural areas that provide a variety of habitat and ecosystem services. Understanding and assessing how coastal landscapes such as this respond to SLR is central to refining adaptive management strategies (Fishman et al., 2014) and identifying areas that provide buffering or mitigation to support long-term management targets (Pelletier et al., 2015).

Coastal environments are products of a complex interplay of exposure and processes, substrate and sediment supply, tidal ranges, and geomorphology (e.g. Davies, 1964; FitzGerald et al., 2008; Hayes, 1979). As illustrated by Carter (1988), a robust body of literature documents the ecologic transition of these environments from the shoreline ~~across increasing slopes and~~ over geomorphic features (e.g. dunes and bluffs) landward. In fact, a relatively ~~stable~~ steady SLR rate over the last few thousand years is central to our modern coastal configuration, including the development of barrier islands and wetlands (e.g., Redfield, 1972; Field & Duane, 1976; Shennan & Horton, 2002), as well as settlement patterns (McGranahan et al., 2007; Liu et al., 2015; Kane et al., 2017). ~~Elevation~~ Because coastal land elevation is primarily governed by the substrate and/or underlying geology of the landscape as well as a product of the physical and biogeochemical processes acting on it, it serves as a central ~~is a key~~ parameter in defining the et al, 2012 and Radic et al., 2013)), and global land water storage (as based on Church et al., 2013). Percentiles of these three components were estimated and then aggregated to provide a SLR scenario and corresponding uncertainty. The projected SLR scenario ranges for each decade used in our model are shown in Figure S1 as follows: 2020s (0 to 0.25 m); 2030s (0.25 to 0.5 m); 2050s (0.5 to 0.75 m) and 2080s (0.75 to 2 m).

AE predictions were generated through implementation of a deterministic equation (see Figure S1~~) by combining~~). First, SLR scenarios ~~from global climate models using IPCC RCPs 4.5 and 8.5 (IPCC, 2013),~~were combined with vertical land movement rates due to subsidence and other non-tectonic effects~~, and~~ (using rates derived from a combination of GPS CORS stations in Sella et al., 2007; and long-term tide gauge data in Zervas et al., 2013) to make projections relative (local). Projected relative SLR values were then subtracted from elevation data, which were comprised of a combination of high-resolution elevation data ~~(Lentz et al., 2015~~from the National Elevation Dataset (NED, Gesch, 2007) supplemented where necessary with coarser resolution bathymetry from the National Oceanic and Atmospheric Administration National Geophysical Data Center's Coastal Relief Model (National Oceanic and Atmospheric Administration, 2014) to predict adjusted land elevation (AE) relative to the projected sea level. ~~Second, dynamic~~ Before model integration, high resolution elevation data were converted to mean high water from North American Vertical Datum 1988 using VDatum conversion grids (National Ocean Service, 2012).

Dynamic response probabilities (DP~~) – the likelihood of an environment to retain its existing state or transition to a new non-submerged state under the given SLR projections –~~) were estimated by coupling the predicted AE ranges with expert knowledge on the response of generalized land cover types (six categories that respond distinctly to SLR ecologically or morphologically~~-~~--subaqueous, marsh, beach, rocky, forest, and developed--as described in Lentz et al. (2015) and shown in Table S1).~~ Because the two response types (inundation and dynamic response) are end members, DP equals one minus the probability of inundation. A DP value of 0.5 indicated highest uncertainty in that either response had an equally likely probability of occurrence (Lentz et al., 2016).~~ Although the resulting predictions provided a robust accounting of uncertainty from some of the data inputs and knowledge of physical landscape change processes, the relative influence of these uncertainties on the predictions has not been explored explicitly.

2.2 Sensitivity and Skill Assessment

We assessed the role of potential error in elevation (E) and land cover (LC) datasets on predicted outcomes. Beaches and estuarine wetlands exist near sea-level; likewise, forests require elevations that provide adequate vadose zone thickness. While this correlation between E and LC allows one to be probabilistically predicted from the other, doing so also results in error~~ correlation~~. Model elevation data came from the National Elevation Dataset (1/9 arc second or 1/3 arc second; U.S. Geological Survey, 2015) and Coastal Relief Model (as described in Lentz et al. 2015). The expected errors in E from these data were included in previous predictions (Lentz et al., 2016), but their effect on predictions was not specifically addressed. Furthermore, the LC values (from McGarrigal et al., 2017) were not treated as uncertain, which was inconsistent with the treatment of all the other relationships in the Lentz et al. (2016) analysis. Better understanding of E and LC error helps to constrain it and identify where better data may improve predictions. Conversely, knowing where data have lower error helps to identify where process uncertainty is highest, which can help prioritize future research efforts.

We expanded our testing to determine 1) how our LC dataset compares with other LC data and previous error quantification results, 2) how E uncertainty is refined by LC information, and 3) where error in LC and E datasets is most likely to affect our predictions.

As described in Lentz et al. (2016), inference training (Bayes rule) was applied in the model to capture the correlation between E and LC in the form:

$$\mathrm{P}(Ei|LCj) = \mathrm{P}(LCj|Ei)x\ \mathrm{P}(Ei)/P(LCj)\ , \tag{1}$$

where we evaluate the ith outcome in the first term on the right as the probabilistic relationship conditioned on inputs from the jth spatial location. Using this relationship, LC, entered with total certainty (such that P(LC_j) is 1.0 if LC_j corresponds to the land cover data at a particular location or P(LC_j) = 0.0 if it does not), updates the prior E, entered with known uncertainty, based on the values of the digital elevation model over the entire modelling domain~~ (Figure 2).~~. Similarly, E data are used to establish conditional probabilities of LC. By assessing potential E and LC error using a BN that implements equation 1 (Figure S1), we can evaluate model skill in reducing error.

2.2.1 Land Cover Data Comparison

As noted in Lentz et al. (2015), the 2010 land cover data in the model (hereafter DSL, after McGarrigal et al., 2017) combine a variety of sources to capture detailed ecosystems information. To better evaluate land cover data error, we compared land cover data with the 2010 Coastal Change Analysis Program (CCAP) land cover dataset which has a quantified error, (NOAA 2017, https://www.coast.noaa.gov/dataregistry/search/collection/info/ccapregional) and were thus used as our "observed" data source. Although the DSL land cover data contain much more detailed ecosystems information than CCAP (19 classes in CCAP vs. 197 classes in DSL), our generalization of DSL data into six classes (Table S1) allowed us to similarly generalize CCAP data and compare the two data sets in terms of user's error (accuracy, or how often the LC type in the DSL data would be the same in the CCAP or "observed" data) and producer's error (reliability, or how often the LC type in the CCAP or "observed" data would be the same in the DSL data). When generalizing the two datasets for purposes of comparison, we further grouped together beach and rocky categories, as both exposed bedrock and beach/dune categories are included in the CCAP "bare land" category (Table S1). Data grids were compared using ArcGIS software's Combine tool (ESRI, 2016).

2.2.2 Model Skill

Our training dataset included E and LC data at ~42,000,000 grid cells throughout the U.S. northeast. We tested our BN (developed with Netica software; Norsys, 2014) and trained on these datasets, to predict E values from LC data, and LC data from E values, by assessing posterior probability distributions in our BN, and evaluating the error rate between predictions and observations. To perform this test, we built a separate two-variable BN to implement equation 1 consisting only of E and LC data (Figure 1). The network was trained on the full elevation and DSL land cover dataset using equation 1, and an error rate was calculated based on the number of times the network predicted a value for a dataset that did not match the observed value at a given location. To test the extension of the inference relationship to situations where E or LC data inputs may be unavailable or limited, the modified BN was used to predict an E value (or LC, as the BNs can be run as both forward and inverse models) as if it were unobserved given only the (uniformly distributed) LC data (or E value) as an input, and the corresponding posterior probabilities were observed.

2.2.3 Mismatch Error

Some errors were expected from inconsistencies between the LC data and the E data, such as where subaqueous categories (Figure 1) co-occurred with elevations above 0 m (referenced to Mean High Water, or MHW in our model), and elevations below 0 m co-occurred with a land cover category other than subaqueous. These mismatches might be due to classification or elevation error, datum changes, or changes over time. To evaluate the impact of these mismatches, we focused on an area contained within the highest resolution and continuous elevation boundary contours (-1 to 10 m from the 1/3 NED), using about half our points (~22,000,000), as we anticipated mismatch errors farther offshore than -1 m would be low (i.e. below 0 m and subaqueous). We classified mismatches by: 1) E data resolution (1/3 and where available, 1/9 arc-second data from the National Elevation Dataset) and 2) LC type to determine whether errors might be explained systematically due to inputs.

Once identified, we examined the effects of mismatches on the accuracy of predicted outcomes. First, our model was used to identify corresponding DP~~ likelihood~~ among LC types and the low-lying E ranges most commonly mistaken with one another (-1 to 0 and 0 to 1 m). Rather than evaluate a specific time step, we made input parameters defining relative SLR uniform (vertical land movement and projected sea level, as in Figure S1) to assess overarching impacts on predictions. Mismatches were also compared geospatially with measured land cover shifts in the 2001 to 2010 CCAP change data (NOAA, 2013) to assess where E and LC data inputs, due to slightly differing dates in their data collection (Lentz et al., 2015) may have captured dynamic state shifts due to process-based changes (e.g. movement of sand bodies around inlets or marsh erosion/inundation; Gomez et al., 2016).

3 Results

3.1 Land Cover Error

Our LC error assessment found 15% error between CCAP and DSL data; this value is the same as the published 15% error for the CCAP dataset (Table ~~S2~~1 and McCombs et al., 2016). ~~Overall, error was highest in~~A confusion matrix (Table S2) reveals which LC classes were most commonly mistaken; most frequent were bare land misclassified as subaqueous, and marsh ~~categories.~~ misclassified as non-marsh vegetation.

In addition to having the lowest number of pixels of all the land cover classes, user's error and producer's accuracy were lowest for the bare land category (49% and 21% respectively); the least number of correctly classified pixels were in the bare land class when compared with the ground truth (CCAP) class. The bare land class also had the least number of pixels when compared with all other LC categories. ~~A confusion matrix (Table S2) reveals which LC classes were most commonly mistaken; most frequent were bare land misclassified as subaqueous, and marsh misclassified as non-marsh vegetation.~~

3.2 Model Skill

The two-parameter BN showed that for this implementation, LC was nearly as useful for constraining E as the other way around (Figure 1; Tables S3-S4). ~~When~~Figure 1a shows that when non-uniform E data were used to predict LC~~ (Figure 1a)~~,, subaqueous environments were the most probable prediction for elevations lower than 0 m~~.~~ (as illustrated by the top four plots on the left). This result reflects, in part, the dominance of subaqueous environments in our data set and therefore strong prior probability that any location below this elevation would be covered by water (Figure S1). Additionally, we developed a modified BN with uniform prior distributions of LC (Figure 1a) and E (Figure 1b) to re-evaluate the inference relationship ~~as if~~under an assumption that all prior states of the nodes were equally probable, which limits prediction bias from the lower percentage representation of certain land cover categories in the region.

Generally (for both original and uniform-prior BNs), elevation signatures specific to different land cover types were observed, with subaqueous, marsh, and beach environments appearing at low-lying elevations, and developed and forested areas showing a predominance for higher elevation settings (Figure 1a). When relying on the original prior LC distribution, the network ~~failed to~~

~~predict correctly three LC types from E data: beaches, rocky, and developed areas, and~~ had a corresponding accuracy rate of 69~~%.~~%, and found, given low-lying elevation as a constraint, beaches and rocky areas were not more probable than another land cover type. Here, beaches were most commonly confused with subaqueous and marsh land cover types~~, developed areas with forests~~, and rocky areas with subaqueous (Table S3a). Uniformly distributed LC priors yielded slightly different predicted outcomes, wherein the network ~~failed to predict~~never found rocky and forested land cover types more probable than another land cover type, most commonly confusing them with subaqueous and developed land cover types respectively (Table S3b). Overall, the accuracy rate in the inference relationship between E and LC was ~~57~~56% when uniform LC prior distributions were used~~.~~ (Table 1).

When land cover data were used to predict elevation (Figure 1b), a consistent dependence of the E distribution on the LC data was seen, with E increasing as LC traversed submerged, marsh, beach, rocky, and forested environments. Overall, accuracy and reliability were lowest for the -1 to 0 m and 0 to 1 m ranges with both original and uniform prior distributions of E (Tables S4a and S4b). The difference in prediction using the uniform-prior BN was ~~relatively small for all inputs except marsh. In the marsh case, the most likely elevation switches from 0-1 m to 5-10 m, which may be in part explained by the fact that when uniform priors were used, the network failed to predict correctly the 0 to 1 m range (most commonly confused with the 1 to 5 m and 5 to 10 m ranges, Table S4b).~~that the 5-10 m range category was predicted, whereas this elevation was not more probable than another when original priors were used. The accuracy rate in the inference relationship between LC and E was 66% for the original prior distribution and ~~59~~58% for the uniform priors~~.~~ (Table 1).

3.3 Mismatch Error

We define a mismatch as a location where the subaqueous LC type co-occurred with elevations above 0 m, or where the remaining LC types co-occurred with elevations below 0 m. The mismatch assessment (Figure 2a) showed that land-water mismatches affect 15% of the reduced (>19,000 km^2) prediction area (Figure 2b) and the most commonly occurring mismatches (Figure 2c) were among dynamic environments (subaqueous, marshes and beaches) at low elevations (-1 to 1 m). More than half of the mismatch data were comprised of LC categories other than subaqueous below 0 m. Of these, nearly all environments were found in the -1 to 0 bin, wherein marshes were the dominant environment type (35% of mismatch), followed by beaches (8% of mismatch). The remaining LC types (rocky, forest, developed) comprised <6% of the observed mismatch area combined. The cumulative probability of the subaqueous category falling in a positive E range (0 to 1 or 1 to 5 m) made up the remainder of the mismatch data (42%), with nearly 78% of these falling within the 0 to 1 m range.

Mismatches helped to highlight what may be systematic offsets with the E and LC data inputs. The most common mismatches were nearly evenly divided between 1/3 and 1/9 arc-second NED datasets, however mismatch error was more dominantly comprised of elevation data below 0 m sourced to the 1/9 arc-sec NED, and error sourced to the 1/3 arc-second dataset most commonly came from the subaqueous category falling in a positive E range. Mismatch error was also nearly three times as likely to occur in marshes or subaqueous categories as in any other LC category (Figure 2b). In sum, mismatches were most concentrated in low-lying ranges for coastal areas 1) comprised of LC categories (beaches, marshes) most commonly misclassified in the LC comparison (Section 3.1) and 2) where land cover was most inaccurate and unreliable when used in predicting elevation (-1 to 1 m, Section 3.2). Using uncertainty terminology as in Mastrandrea et al., 2010, mismatched beaches had a *likely* DP (P > 0.66) in both -1 to 0 and 0 to 1 m bins (Figure 2d), whereas the DP for the remaining mismatched land cover categories between -1 to 1 m were *as likely as not* (0.33 < P < 0.66; marshes, forests) to *unlikely* (P > 0.33; rocky, developed).

4 Discussion

The high overall agreement between CCAP and DSL data when reclassified (Table S1) indicates DSL data have at most moderate error. Although the elevation data have a stated, calculated error that was integrated directly in our model, a similar error estimate was not available for the land cover (DSL) data (although our probabilistic framework allows this to be incorporated if available). Comparing the DSL land cover dataset to a dataset with a known error value (CCAP), revealed an identical error rate (15%) to that determined for CCAP alone (McCombs et al., 2016). Although we cannot confirm that this error resides solely with the CCAP data, the updated and more detailed information in the DSL data, as well as the similarity in error rate with the published CCAP error, suggests that entering the DSL data as if they are known with certainty is an appropriate assumption for most of our LC categories.

The land cover comparison also showed that bare land and marsh categories are those most commonly classified as another category (subaqueous and non-marsh vegetation respectively). The greatest error in the comparison--the bare land category~~--might be~~—is in part explained by the substantial under-representation of beaches in both datasets when compared with other LC types. ~~Here our~~ Due to this under-representation, beaches are never the most probable land cover type predicted from E when original prior distributions are applied (Table 3a). Our uniform prior test ~~provides insight as to the influence~~demonstrates that in spite of this regional bias~~; when the beach LC type is~~, there is also ambiguity in the E-LC relationship in with regards to beaches and marshes in our model; when either marshes are beaches are predicted from E with a uniform prior, ~~it matches~~they match the observed LC (user's accuracy) ~~13~~47-49% of the time respectively (Table S3b~~), demonstrating considerable ambiguity in the E-LC relationship. Using~~). However, beaches are more confidently predicted in the -1 to 0 m range than other land cover types (Figure 1b), suggesting a propensity of beaches in our model training data are shallowly submerged. Incorporating first-return lidar instead of bare earth data in our model could be used to further distinguish the six LC types from one another via vegetation differences (e.g. Lee and Shan, 2003; Im et al., 2008; Reif et al., 2011) and better distinguish intertidal areas, which may allow refinement of marsh, beach, and forest classifications (e.g. Kepeneers et al., 2009; Sturdivant et al., 2017).

Testing our two-node BN revealed that Bayesian inference can be used to fill data gaps or enhance data quality. Applying both non-uniform and uniform priors (the latter to remove the regional land cover biases specific to the northeastern U.S.) showed that land cover-specific elevation signatures are present. Notable distinctions were between elevation end members (very high or very low relief; subaqueous, forests, developed) and mid-range (moderate relief; marshes, beaches, rocky) areas. ~~A high marsh signature was also present, however, making this LC type more difficult to distinguish from forest and developed LC types based on elevation.~~ Assessing model skill in the E and LC relationship revealed an accuracy of ~~57~~56% (uniform priors) to 69% (non-uniform priors), showing that including the regional LC bias helped to improve predictions~~,~~ (Table 1), and that the most commonly missed LC-E predictions occurred in elevations closest to mean sea level (-1 to 1 m).

In addition to missed predictions, our testing revealed that some E ranges and LC categories were never the most probable outcome. This was true for several land cover types (specifically beaches and rocky under original E priors; rocky and forest under uniform priors (Tables S3) and one elevation range (5-10 m elevations under original LC priors, Table S4b). For the original priors, we attribute this to the under-representation of certain classes (regional bias) in our training data, wherein beaches, rocky, and 5-10 m elevation ranges were infrequent when compared to other classes/bins. In the case of uniform priors, our BN is detecting the slightly stronger relationship of some land cover types in certain elevation ranges (e.g. developed in the 1 to 5 m range), thereby making other E-LC relationships never more probable than these. Although bin reassignments that span smaller elevation ranges could help resolve more specific land cover signatures in our model, particularly for low-lying beaches and marshes, this would likely occur at the cost of increased prediction uncertainty as outcomes would span a larger number of bins.

Our mismatch analysis revealed LC and E mismatches are uncommon and found at low elevations (-1 to 1 m) in dynamic environments (beaches, marshes, and subaqueous categories). Mismatches were most infrequent among typically higher elevation environments (forests, developed, and rocky). We suggested that low elevation mismatches resulted from physical changes, such as tidal inlets causing submerged sandbars to become subaerial beach, or forests becoming marshes. However, comparison with CCAP changes from 2001 to 2010, revealed a very small (3%) correspondence with identified areas of mismatch. Results instead may suggest high-resolution (1/9 NED) E data captures a systematic offset in part due to MHW submergence from datum conversion (~~from NAVD88;~~ Lentz et al., 2015), particularly for marshes and beaches (Fig 3b). In addition to elevation data that accounts for vegetation, as suggested earlier, seamless and continuous topographic and bathymetric data (Danielson et al., 2016) would constrain resolution error and better resolve distinctions between subaerial and subaqueous environments.

Ultimately, the contributions of data error are unlikely to change the DP uncertainty categories (Fig. ~~3d~~2d). In the case of LC error, the most commonly confused LC categories were subaqueous with beach categories, and marshes with forests. In either case, when coupled with E data, beaches and subaqueous categories between -1 and 1 m generally have a *likely* DP and marshes and forests to have an *as likely as not* DP (Figure 2d), with the latter emphasizing the dominance of process uncertainty as accounted for in our original model via expert elicitation (as described in Lentz et al., 2015) over data error in affecting DP outcomes. Furthermore, the response of developed and some beach areas to SLR is also particularly uncertain in our model due to unknowns regarding human behaviour (Wong et al., 2014). Socioeconomic factors (McNamara et al., 2011, Hinkel et al., 2013) may determine where buildings and critical infrastructure are adapted to a dynamically changing landscape, coastal engineering projects are employed or upgraded (Gedan et al., 2011; Arkema et al., 2013), and alternatives such as inland migration (Hauer et al., 2016; 2017) or managed retreat occur. Our probabilistic modelling framework allows us to update likelihood predictions as more information about the SLR response of the coastal landscape, and people living on it, becomes available.

5 Conclusions

Our results show that a) land cover error between two data sources is consistent with published error for one source (15%), b) inference training further reduces error, and c) mismatch error is low with respect to the prediction area. To better resolve elevation and land cover distinctions in low-lying environments, elevation that accounts for vegetation distinctions, and/or seamless datasets including both topography and bathymetry may be useful. However, the ability to capture the relationship between elevation and land cover via Bayesian inference in such a sizeable region demonstrates that it is possible to extend this application where data restrictions or gaps might otherwise limit expansion.

Furthermore, data input error has minimal effect on our predicted outcomes, particularly when uncertainty terminology is applied (Figure 2d). These outcomes therefore support first-order decision-making surrounding the inundation potential of specific environments, providing an essential risk assessment tool (NRC, 2009). We find uncertainty in the response of different land cover types to varying SLR scenarios in our coastal response model is composed dominantly of uncertainty in physical and ecological processes, as opposed to data error, particularly for developed areas and low elevation marshes (Lentz et al., 2016). To further refine assessments of future coastal response in areas of concern, data or deterministic models that account for site-specific SLR response rates and process knowledge will be well-paired with this approach.

Data Availability

Coastal response outcomes: Lentz, E.E., Stippa, S.R., Thieler, E.R., Plant, N.G., Gesch, D.B., and Horton, R.M. 2015, Coastal landscape response to sea-level rise assessment for the northeastern United States (ver. 2.0., December 2015): U.S. Geological Survey data release, http://dx.doi.org/10.5066/F73J3B0B.

Supplement link (tbd)

Author Contributions

EEL and NGP designed the study; EEL the conducted analysis; and EEL, ERT, and NGP drafted the initial version of the manuscript. All authors discussed results and contributed to later versions of the manuscript.

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References

Arkema, K.K., Guannel, G., Verutes, G., Wood, S.A., Guerry, A., Ruckelshaus, M., Karejva, M., Lacayo, M., and Silver, J.M.: Coastal habitats shield people and property from sea-level rise and storms. *Nat. Clim. Change, 3*, 913-918. https://doi.org/10.1038/nclimate1944, 2013.

Cahoon, D.R., Reed, D.J., Kolker, A.S., Brinson, M.M., Stevenson, J.C., Riggs, S., Christian, R., Reyes, E., Voss, C., & Kunz, D.: Coastal wetland sustainability. In J.G. Titus, K.E. Anderson, D.R. Cahoon, D.B Gesch, S.K. Gill, B.T. Gutierrez, B.T., E.R. Thieler, & S.J. Williams, *Coastal sensitivity to sea-level rise— A focus on the mid-Atlantic region*: Washington, D.C., U.S. Environmental Protection Agency, pp. 57– 72, 2009.

Carter, R.: *Coastal environments: an introduction to the physical, ecological, and cultural systems of coastlines.* Academic: San Diego, CA, 1988.

Church, J.A., Clark, P.U., Cazenave, A., Gregory, J.M., Jevrejeva, S., Levermann, A., Merrifield, M.A., Milne, G.A., Nerem, R.S., Nunn, P.D., Payne, A.J., Pfeffer, W.T., Stammer, D., & Unnikrishnan, A.S.: Sea level change. In T.F. Stocker, D. Qin, G-K Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, V., & P.M. Midgley, (Eds.), *Climate Change 2013: The Physical Science Basis* (Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change). Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, 2013.

Danielson, J.J., Poppenga, S.K., Brock, J.C., Evans, G.A., Tyler, D.J., Gesch, D.B., Thatcher, C.A., and Barras, J.A.: Topobathymetric elevation model development using a new methodology-Coastal National Elevation Database. *J. Coastal Res.*, *SI*(76), 75-89. http://dx.doi.org/10.2112/SI76-008, 2016.

Davies, J.L.: A morphogenic approach to world shorelines. *Z. Geomorphol.*, *8*, 27-42, 1964.

ESRI: ArcGIS Desktop: Release 10. Redlands, CA: Environmental Systems Research Institute, 2016.

Ezer, T. and Atkinson, L. P.: Accelerated flooding along the U.S. East Coast: On the impact of sea-level rise, tides, storms, the Gulf Stream, and the North Atlantic Oscillations. *Earth's Future, 2*, 362–382, 2014.

Fischman, R.L., Meretsky, V.J., Babko, A., Kennedy, M., Liu, L., Robinson, M., and Wambugu, S.: Planning for adaptation to climate change: Lessons from the US National Wildlife Refuge System. *BioScience, 64*(11), 993-1005, 2014.

FitzGerald, D.M., Fenster, M.S., Argow, B.A., and Buynevich, I.V.: Coastal impacts due to sea-level rise. *Annu. Rev. of Earth Planet. Sci.*, *36*(1), 601-647, 2008.

Field, ME., and Duane, D.B.: Post-Pleistocene history of the United States inner continental shelf: Significance to origin of barrier islands. *Geol. Soc. Am. Bull.*, *87*(5): 691–702, 1976.

Gedan, K.B., Kirwan, M.L., Wolanski, E., Barbier, E.B. & Silliman, B.R: The present and future role of coastal wetland vegetation in protecting shorelines: Answering recent challenges to the paradigm. *Clim. Change*, 7-29, 2011.

Gesch, D.B, The national elevation dataset, chap. 4 of Maune, D.F., ed., *Digital elevation model technologies and applications—The DEM users manual (2d ed.)* (pp.99-118). Bethesda, Md.: American Society for Photogrammetry and Remote Sensing.

Gesch, D.B.: Analysis of lidar elevation data for improved identification and delineation of lands vulnerable to sea-level rise. *J. Coastal Res., SI*(53), 49-58, 2009.

Gomez, C., White, J.C., and Wulder, M.A.: Optical remotely sensed time series data for land cover classification: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *116*, 55-72, 2016.

Hayes, M.O.: Barrier island morphology as a function of tidal and wave regime, In S.P Leatherman (Ed.), *Barrier Islands from the Gulf of St. Lawrence to the Gulf of Mexico* (pp. 1-27). New York, NY: Academic, 1979.

Goddard, P.B., Yin, J., Griffies, S.M., and Zhang, S.: An extreme event of sea-level rise along the Northeast coast of North America in 2009-2010. *Nat. Commun.*, 6, 6346, 2015.

Hauer, M.E., Evans, J.M., and Mishra, D.R.: Millions projected to be at risk from sea-level rise in the continental United States. *Nat. Clim. Change*, 6, 691-695, 2016.

Hauer, M.E.: Migration induced by sea-level rise could reshape the US population landscape. *Nat. Clim. Change*, 7, 321-325, 2017.

Hinkel, J., Lincke, D., Vafeidis, A.T., Perrette, M., Nicholls, R.J., Tol, R.S. J., Marzeion, B., Fettweis, X., Ionescu, C., and Levermann, A.: Coastal flood damage and adaptation costs under 21st century sea-level rise. *Proceedings of the National Academy of Sciences*, 111(9), 3292-3297, 2014.

Im, J., Jensen, J.R., and Hodgson, M.E.: Object-based land cover classification using high-posting-density lidar data. *GIScience and Remote Sensing*, 45(2), 209-228, 2008.

Kane, H., Fletcher, C., Cochrane, E., Mitrovica, J., Habel, S., and Barbee, M.: Coastal plain stratigraphy records tectonic, environmental, and human habitability changes related to sea-level drawdown, 'Upolu, Samoa. *Quat. Res.*, 87(2), 246-257, 2017.

Kempeneers, P. Deronde, B., Provoost, S. and Houthuys, R.: Synergy of airborne digital camera and lidar data to map coastal dune vegetation. *J. Coastal Res.*, SI 53, 73-82, 2009.

Kirwan, M.L. and Megonigal, J.P.: Tidal wetland stability in the face of human impacts and sea-level rise. *Nature*, 504, 53-60, 2013.

Kopp, R.E.: Does the mid-Atlantic United States sea level acceleration hot spot reflect ocean dynamic variability? *Geophys. Res. Lett.*, 40(15), 3981-3985, 2013.

Kopp, R. E., Horton, R. M., Little, C. M., Mitrovica, J. X., Oppenheimer, M., Rasmussen, D. J., Strauss, B. H. and Tebaldi, C.: Probabilistic 21st and 22nd century sea-level projections at a global network of tide-gauge sites. *Earth's Future*, 2, 383–406, 2014.

Lee, D.S. & Shan, J.: Class-guided building extraction from Ikonos imagery. *Photogrammetric Engineering & Remote Sensing*, 2, 143-150, 2013.

Lentz, E.E., Thieler, E.R., Plant, N.P, Stippa, S.R., Horton, R., and Gesch, D.B.: Evaluation of dynamic coastal response to sea-level rise modifies inundation likelihood. *Nat. Clim. Change*, 6, 696-700, 2016.

Lentz, E.E., Stippa, S.R., Thieler, E.R., Plant, N.G., Gesch, D.B., and Horton, R.M.: *Evaluating coastal landscape response to sea-level rise in the northeastern United States—Approach and methods* (OFR 2014-1252). U.S. Geological Survey, 2015.

Liu, J., Wen, J., Huang, Y., Shi, M., Meng, Q., Ding, J., Xu, H.: Human settlement and regional development in the context of climate change: A spatial analysis of low elevation coastal zones in China. *Mitigation and Adaptation Strategies for Global Change*, 20(4), 527-546, 2015.

Marcy, D, Brooks, W., Draganov, K., Hadley, B., Haynes, C., Herold, N., McCombs, J., Pendleton, M., Ryan, S., Schmid, K., Sutherland, M., & Waters, K.: New mapping tool and techniques for visualizing sea-level rise and coastal flooding impacts, in: Wallendorf, L., Jones, C., Ewing, L., and Battalio, B. (Eds.), *Solutions to Coastal Disasters 2011*, American Society of Civil Engineers, Reston, VA, 474–490,: 2011.

Marzion, B., Jarosch, A.H., and Hofer, M.: Past and future sea-level change from the surface mass balance of glaciers: *The Cryosphere*, 6(6), 1295–1322, 2012.

Mastrandrea, M.D., Field, C.B., Stocker, T.F., Edenhofer, O., Ebi, K.L., Frame, D.J., Held, H., Kriegler, E., Mach, K.J., Matschoss, P.R., Plattner, G.-K., Yohe, G.W., and Zwiers, F.W.: *Guidance Note for Lead Authors of the IPCC Fifth Assessment Report on Consistent Treatment of Uncertainties*. Intergovernmental Panel on Climate Change (IPCC), 2010.

McCombs, J.W., Herold, N.D., Burkhalter, S.G, and Robinson, C.J.: Accuracy assessment of NOAA Coastal Change Analysis Program 2006-2010 Land Cover and Land Cover Change Data. *Photogrammetric Engineering and Remote Sensing*, 82(9), 711-718, 2016.

McGarigal K, Compton BW, Plunkett EB, Deluca WV, & Grand J.: *Designing sustainable landscapes: DSLland and Subsysland.* Report to the North Atlantic Conservation Cooperative, US Fish and Wildlife Service, Northeast Region: (http://jamba.provost.ads.umass.edu/web/LCC/DSL_documentation_DSLland.pdf), 2017.

McGranahan, G., Balik, D., and Anderson, B.: The rising tide: assessing the risks of climate change and human settlements in low elevation coastal zones. *Environment and Urbanization*, 19, 17-37, 2007.

McNamara, D.E., Murray, A.B. and Smith, M.D.: Coastal sustainability depends on how economic and coastline responses to climate change affect each other. *Geophys. Res. Lett.*, 38, L07401: 1-5, 2011.

Mitrovica, J.X., Gomez, N., Morrow, E., Hay, C., Latychev, K., and Tamisiea, M.E.: On the robustness of predictions of sea level fingerprints. *Geophys. J. Int.*, 187, 729-742, 2011.

National Research Council: Science and Decisions: Advancing Risk Assessment. The National Academies Press, Washington DC: 422 p., 2009.

National Oceanic and Atmospheric Administration National Geophysical Data Center, U.S. coastal relief model: National Oceanic and Atmospheric Administration National Geophysical Data Center Web page, last access 9 June 2014 at http://www.ngdc.noaa.gov/mgg/coastal/crm.html.

National Oceanic and Atmospheric Administration, Office for Coastal Management. 2010 Coastal Change Analysis Program (C-CAP) Regional Land Cover. www.coast.noaa.gov/ccapftp, last access: 5 June 2017.

NOAA's Coastal Change Analysis Program (C-CAP) 2001 to 2010 Regional Land Cover Change Data - Coastal United States: Department of Commerce (DOC), National Oceanic and Atmospheric Administration (NOAA), National Ocean Service (NOS), Office for Coastal Management (OCM), https://coast.noaa.gov/dataregistry/search/dataset/info/ccapregional, 2013, last access: 5 June 2017.

Norsys, 1992-2013. Netica 5.12.

Pelletier, J.D., Murray, A.B., Pierce, J.L., Bierman, P.R., Breshears, D.D., Crosby, B.T., Ellis, M., Foufoula-Georgiou, E.,Himsath, A.M., Houser, C., Lancaster, N., Marani, M., Merritts, D.J., Moore, L.J., Pederson, J.L., Poulous, M.J., Rittenour, T.M., Rowland, J.C., Ruggiero, P., Ward, D.J., Wickert, A.D., Yager, E.M.: Forecasting the response of Earth's surface to future climatic and land use changes: A review of methods and research needs. *Earth's Future*, 3, 220-251, 2015.

Radić, V., Bliss, A., Beedlow, C.D., Hock, R., Miles, E., and Cogley, J.G.: Regional and global projections of twenty-first century glacier mass changes in response to climate scenarios from global climate models: *Climate Dynam.* 42 (1–2), 37–58, 2013.

Redfield, A.C.: Development of a New England salt marsh. *Ecol. Monogr.*, 42, 201–237, 1972.

Reif, M.K., Macon, C.L., Wozencraft, J.M., Post-Katrina land cover, elevation, and volume change assessment along the south shore of Lake Pontchartrain, Louisiana, U.S.A. *J. Coastal Res.*, SI 62, 30-39, 2011.

Sella, G.F., Stein, Seth, Dixon, T.H., Craymer, Michael, James, T.S., Mazzotti, Stephane, and Dokka, R.K.: Observation of glacial isostatic adjustment in "stable" North America with GPS. *Geophys. Res. Lett.*, 34(2), L02306, 6 p., 2007.

Shennan, I., and Horton, B.: Holocene land- and sea-level changes in Great Britain. *Journal of Quaternary Science*, 17(5-6), 2002.

Slangen, A.B.A., Church, J.A., Zhang, X., and Monselesan, D.: Detection and attribution of global mean thermosteric sea level change. *Geophys. Res. Lett.*, 41: 5951-5959, 2014.

Strauss, B.H., Ziemlinski, R., Weiss, J.L., and Overpeck, J.T.: Tidally adjusted estimates of topographic vulnerability to sea level rise and flooding for the contiguous U.S. *Environ. Res. Lett.*, 7, 014033, 2012.

Sturdivant E., Lentz E.E., Thieler, E. R, Farris, A., Weber, K., Remsen, D., Miner, S., & Henderson R.: UAS-SfM for coastal research: Geomorphic feature extraction and land cover classification from high-resolution elevation and optical imagery. *Remote Sens.*, 9 (10), 1020, 2017.

Sweet, W. V. and Park, J.: From the extreme to the mean: Acceleration and tipping points of coastal inundation from sea level rise. *Earth's Future*, 2, 579–600, 2014.

Sweet, W. V., Kopp, R.E., Weaver, C.P., Obeysekera, J., Horton, R.M., Thieler, E.R., and Zervas, C.: *Global and Regional Sea Level Rise Scenarios for the United States*. NOAA Technical Report NOS CO-OPS 083. NOAA/NOS Center for Operational Oceanographic Products and Services, 75 p., 2017a.

Sweet, W.V., Horton, R., Kopp, R.E., LeGrande, A.N., and Romanou, A.: Sea Level Rise. In D.J. Wuebbles, D.W. Fahey, K.A. Hibbard, D.J. Dokken, B.C Stewart, & T.K. Maycock (Eds.), *Climate Science Special Report: Fourth National Climate Assessment, Volume 1* (pp. 333-363). U.S. Global Change Research Program: Washington DC: 2017b.

Taylor, K.E., Stouffer, R.J., and Meehl, G.A.: An overview of CMIP5 and the experiment design: *B. Am. Math. Soc.*, 93(4), p.

485–498, 2012.
U.S. Geological Survey: NED spatial metadata: http://ned.usgs.gov/downloads.html, last accessed: 2 January 2015.
Wong, P.P., Losada, I.J., Gattuso, J.-P., Hinkel, J., Khattabi, A., McInnes, K.L., Saito, Y., and Sallenger, A.: Coastal systems and low-lying areas. In C.B. Field, V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L.White (Eds.). *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects* (pp. 361-409). Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press: Cambridge, United Kingdom and New York, NY, USA: 2014.
Yin, J., and Goddard, P.B.: Oceanic control of sea level rise patterns along the East Coast of the United States. *Geophys. Res. Lett.*, 40, 5514–5520, 2013.
Yin, J., Schlesinger, M.E., and Stouffer, R.J.:Model projections of rapid sea-level rise on the northeast coast of the United States. *Nat. Geosci.*, 2: 262-266, 2009.
Zervas, C., Gill, S., and Sweet, W.: *Estimating Vertical Land Motion from Long-Term Tide Gauge Records*. NOAA Technical Report NOS CO-OPS 065, 30 p., 2013.

~~Figures~~

Confusion Matrix	**Accuracy Rate**
C-CAP vs. DSL Land Cover comparison	85%
Predicted vs. Observed Land Cover *Elevation inputs; original distributions*	77%
Predicted vs. Observed Land Cover *Elevation inputs; uniform distributions*	65.5%
Predicted vs. Observed Elevation *Land Cover inputs; original distributions*	66%
Predicted vs. Observed Elevation *Land cover inputs; uniform distributions*	59%

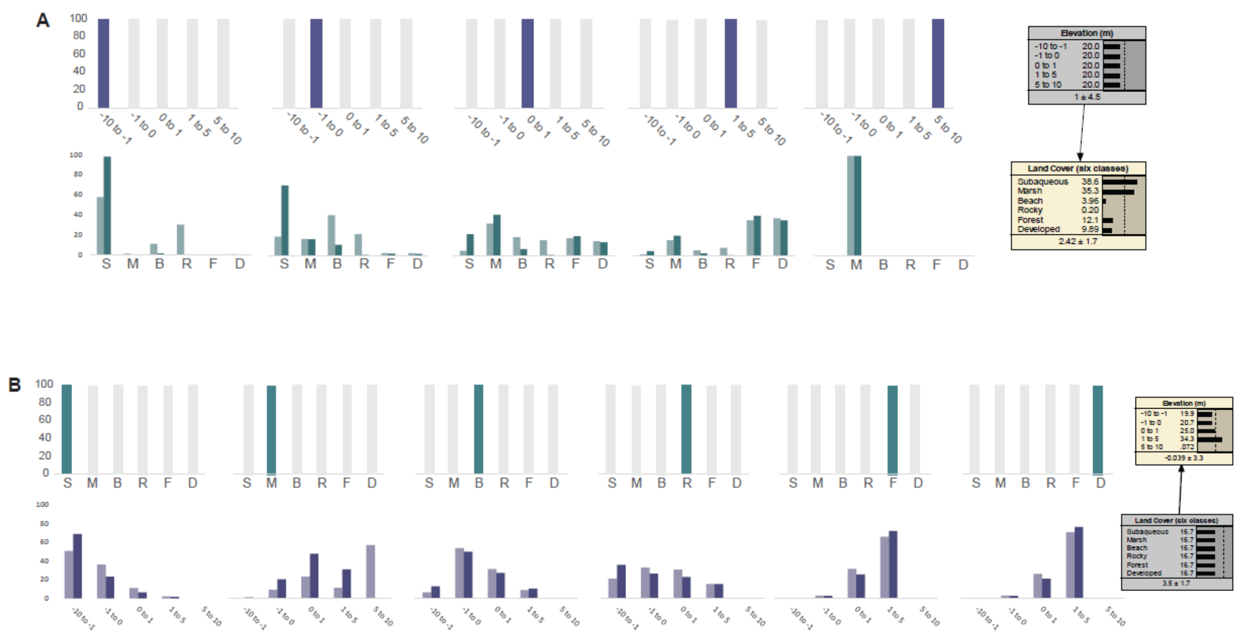

Table 1. Summary table of accuracy rates for all confusion matrices of land cover and elevation comparisons. Accuracy rates are calculated by summing where predictions matched observations (the diagonal bolded terms in Tables S2-S4) and dividing by the total number of outcomes. Confusion matrices are available in supplemental materials (Tables S2-S4).

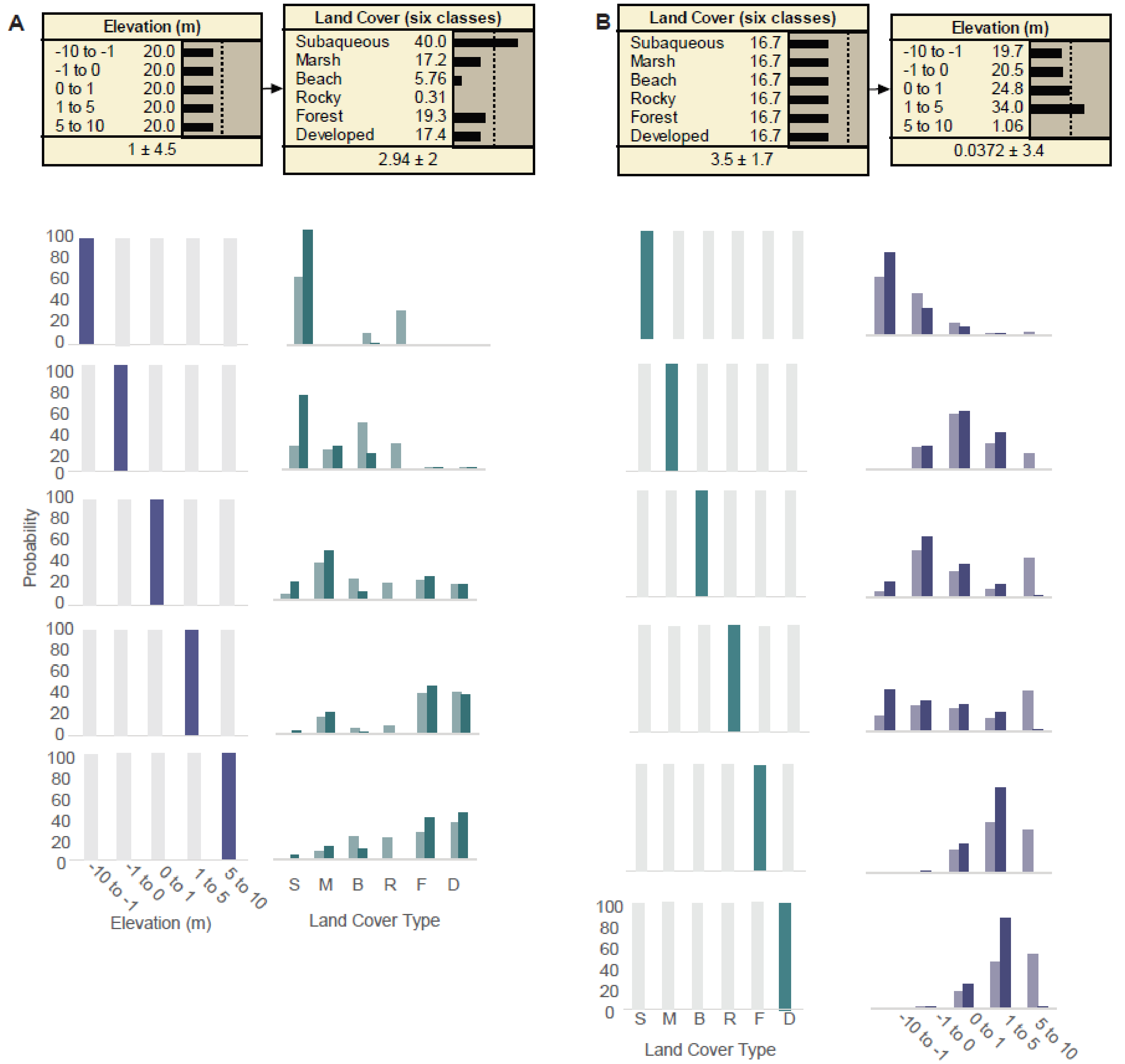

Figure 1. Updated probability distributions after training between elevation and land cover datasets with non-uniform (dark) and uniform (light) priors (the latter to limit regional LC bias), a) showing land cover distributions under selected elevation ranges and b) showing elevation distributions under selected land cover types. Land cover categories (Table S1) abbreviated as follows: S = subaqueous; M = marsh; B = beach; R = rocky; F = forest; and D = developed.

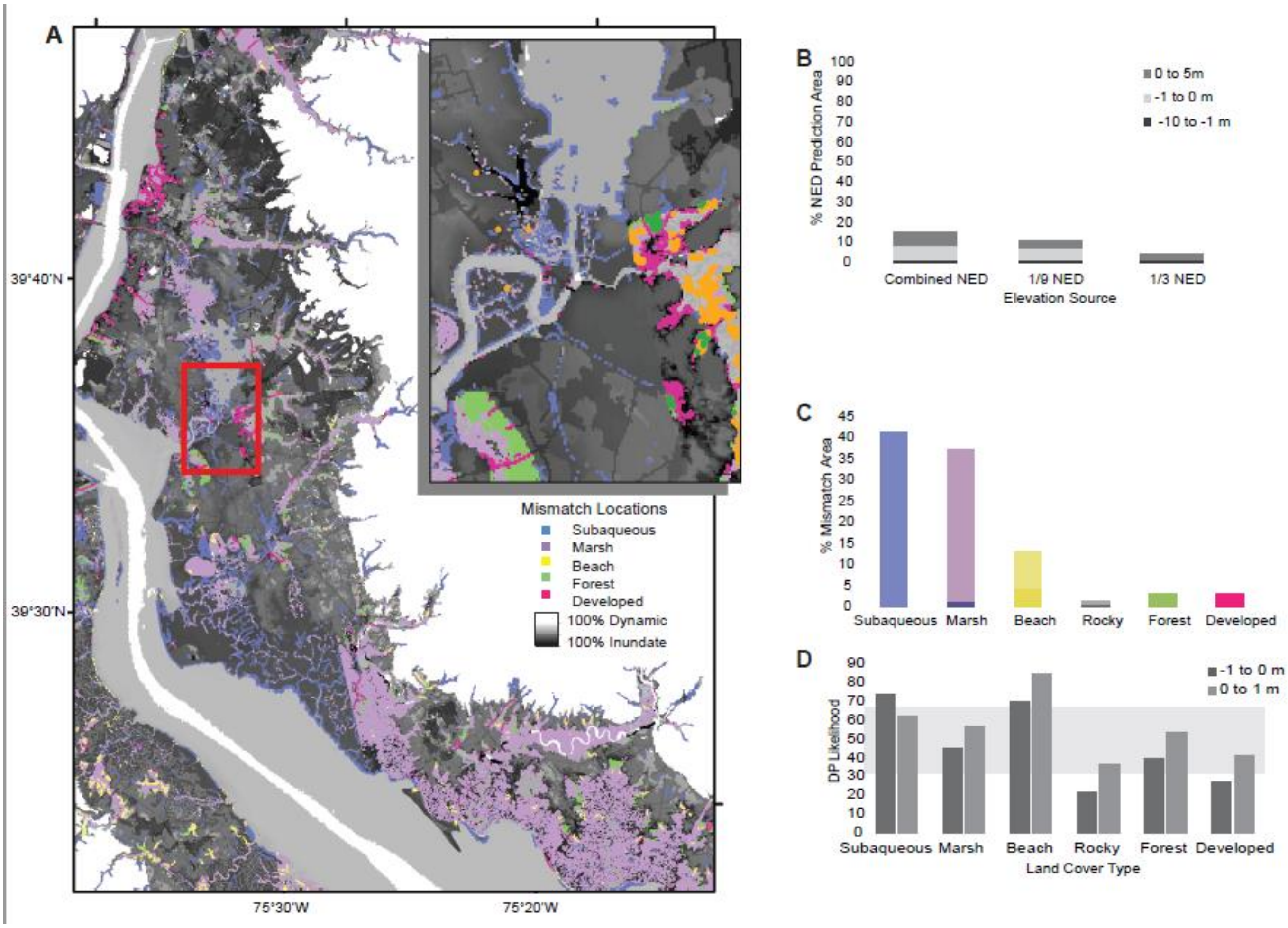

Figure 2. Results of mismatch analysis a) in selected area with inset of enlarged view; b) shown as percentage of the prediction area within the 1/3 National Elevation Dataset (NED) contour boundary and by elevation source type; c) by land cover type as a percentage of the total mismatch area, where lighter hues show the percent of predictions in the -1 to 0 m range (with the exception of subaqueous, which shows a 0 to 1 m range), and darker hues show the percent of predictions in the -10 to 1 m range; and d) the corresponding DP ~~likelihood~~ for each land cover type in the elevation ranges most commonly mistaken (light gray box shows the as likely as not 0.33>P>0.66 range).