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](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 will add 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. Our suggested change is as follows:

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 will revise the text from "skillfulness" to "skill" as suggested.

Page 2, line 26: Reduces?

We will replace "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, we propose to revise the sentence as follows to clarify our intent:

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 will add 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 suggested revisions correspond to the revised version of the figure as attached to this document and would be submitted as part of the revised manuscript.

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 are attaching these corrected tables and a revised Figure 1 to this document so that they may be compared with the originals to illustrate the changes, and we will make minor corrections to the corresponding areas in the manuscript that cites these numbers in resubmission. Specifically:

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

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

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, we will include a new table that summarizes all accuracy rates. The new table (Table 1) included here and will be 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 will include mention of this lack of prediction of certain land cover types and the reasons behind it in a revised manuscript to enhance our discussion. Our suggested changes include:

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 will add text to the methods section to clarify this adjustment. Specifically:

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. If we are invited to submit a revised manuscript, we will add detail to the discussion section to reflect this insight such as:

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

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 will be sure to include more detail regarding how the model works in a revised submission. Our comments to follow detail how we will incorporate more specific information in our revision. In addition to these changes, we will revisit 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 will revise the Previous Work section in Data and Methods to provide detail as suggested including the following:

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 will remove "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 will be 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 will be 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 included at the end of this document and will be included 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 will replace "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 outcomes " will be reworked to be more specifically defined to the overall probability of dynamic response. Specifically:

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 will modify the text to provide more specificity regarding these ranges and their time correspondence. Specifically, we propose the following:

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 will include these details and references to the citations below to provide the reader this context in a revised submission. Specifically:

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 will add additional detail the caption to make this point clear. Specifically:

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:

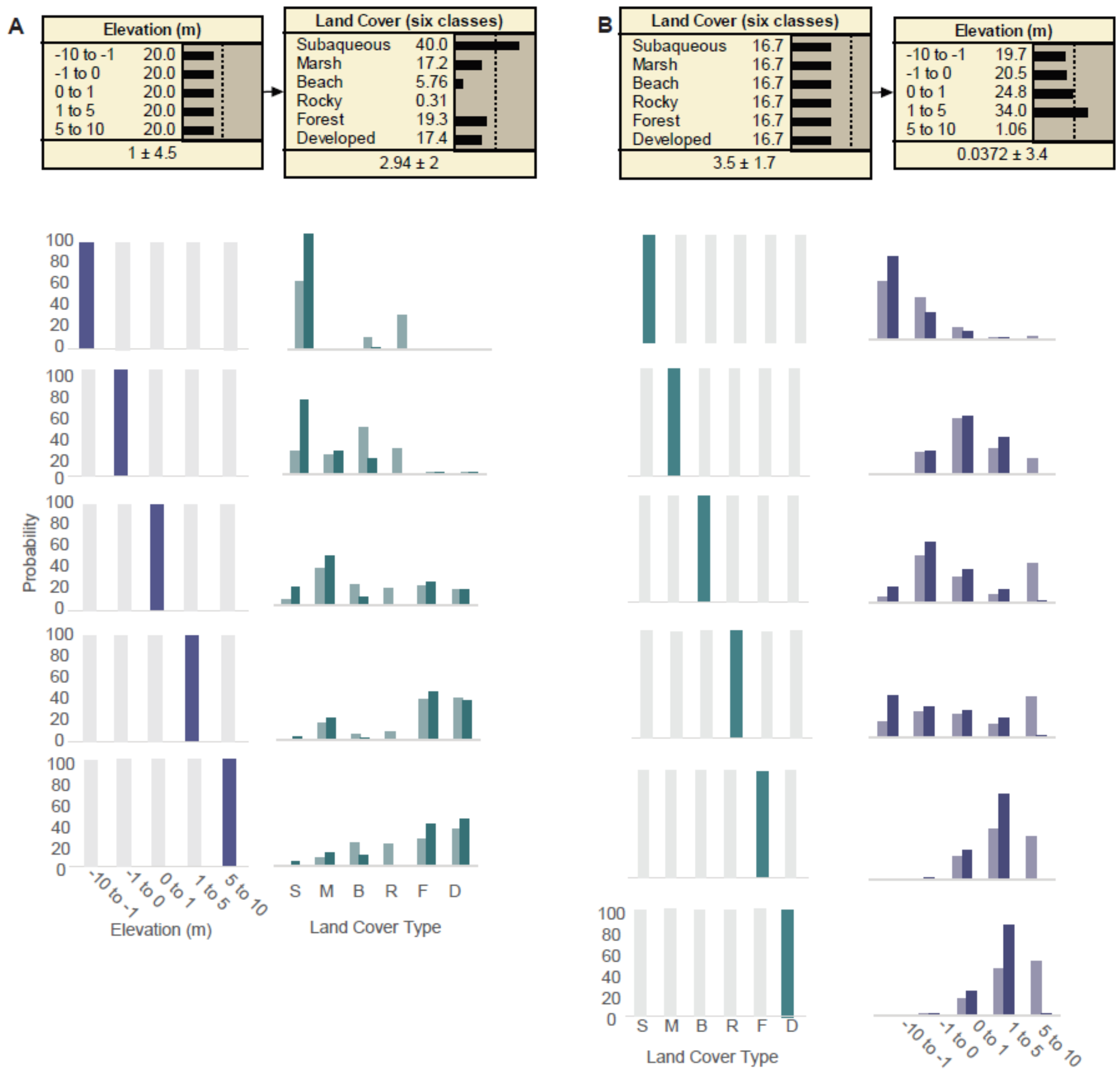

Figure 1. Updated probability distributions after training between elevation and land cover datasets with non-uniform (dark) and uniform (light) priors (the latter to limit regional LC bias), a) showing land cover distributions under selected elevation ranges and b) showing elevation distributions under 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%.