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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 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 is a key parameter in defining the distribution and configuration of coastal ecosystems and their ability to evolve in response to processes driving change (Gesch, 2009; Kempeneers et al., 2009).

Models are widely available (e.g., Marcy et al. 2011, Strauss et al. 2012) to estimate the potential for SLR-induced inundation across the landscape. These models use present-day elevation as a primary input, which makes them well-suited to identify impacts to developed areas, where hard structures, barriers to migration, and other stabilization measures constrain the landscape to its current elevation and use. However, these models cannot depict landscape variability in environments that respond dynamically to SLR through mechanisms such as vertical accretion due to washover or biomass accumulation. Lentz et al. (2016) addressed this limitation by developing a coastal response model (Figure 2) for the northeastern U.S. that predicts the likelihood of dynamic response to SLR, where *dynamic* is defined as the ability of an environment to either maintain its current state (e.g., a beach remains a beach) or transition to another non-submerged state (e.g., a forest becomes a marsh).

The confidence of our probabilistic SLR predictions depends on the accuracy of model input parameters, which include continuous land cover and elevation data. Here, we use the nearly 38,000 km^2 coverage of Lentz et al. (2016) to examine 1) the sensitivity of predictions to differences in the certainty of these input data and 2) model skilfulness to determine where better data would improve prediction confidence and affect results. We explore the inherent correlation between elevation and coastal land cover distributions in our model by testing the ability of Bayesian inference to capture this relationship such that elevation may be used to predict land cover, and vice versa. We hypothesize that the relationship between these data inputs over such an extensive and diverse expanse refines uncertainty in each parameter in our framework and that, relative to process uncertainty, error in these datasets has negligible impact on predicted outcomes. In addition to better understanding model sensitivity to these parameters, our results also clarify how Bayesian inference may be used to supplement poorer data quality and/or uncertainty, particularly in low-lying coastal environments.

2 Data and Methods

2.1 Previous Work

Lentz et al. (2015) mapped coastal response outcomes using a Bayesian network (BN) probabilistic modelling approach. 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 produced two outcomes at a 30 x 30 m resolution for the 2020s, 2030s, 2050s, and 2080s (Figure S1). The first generated inundation predictions through implementation of a deterministic equation (see Figure S1) by combining SLR scenarios from global climate models using IPCC RCPs 4.5 and 8.5 (IPCC, 2013), vertical land movement rates due to subsidence and other non-tectonic effects, and high-resolution elevation data (Lentz et al., 2015) to predict adjusted land elevation (AE) relative to the projected sea level. Second, 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 as 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 i^{th} outcome in the first term on the right as the probabilistic relationship conditioned on inputs from the j^{th} spatial location. Using this relationship, LC, entered with total certainty (such that $P(LC_j)$ is 1.0 if LC_j corresponds to the

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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 and McCombs et al., 2016). Overall, error was highest in bare land and marsh categories. 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 E data were used to predict LC (Figure 1a), subaqueous environments were the most probable prediction for elevations lower than 0 m. This result reflects, in part, the dominance of subaqueous environments in our data set and 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 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%. 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 rocky and forested land cover types, 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% when uniform LC prior distributions were used.

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). The accuracy rate in the inference relationship between LC and E was 66% for the original prior distribution and 59% for the uniform priors.

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 explained by the substantial under-representation of beaches in both datasets when compared with other LC types. Here our uniform prior test provides insight as to the influence of this regional bias; when the beach LC type is predicted from E with a uniform prior, it matches the observed LC (user's accuracy) 13% of the time (Table S3b), demonstrating considerable ambiguity in the E-LC relationship. 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) 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% (uniform priors) to 69% (non-uniform priors), showing that including the regional LC bias helped to improve predictions, and that the most commonly missed LC-E predictions occurred in elevations closest to mean sea level (-1 to 1 m).

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). 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 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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Figures

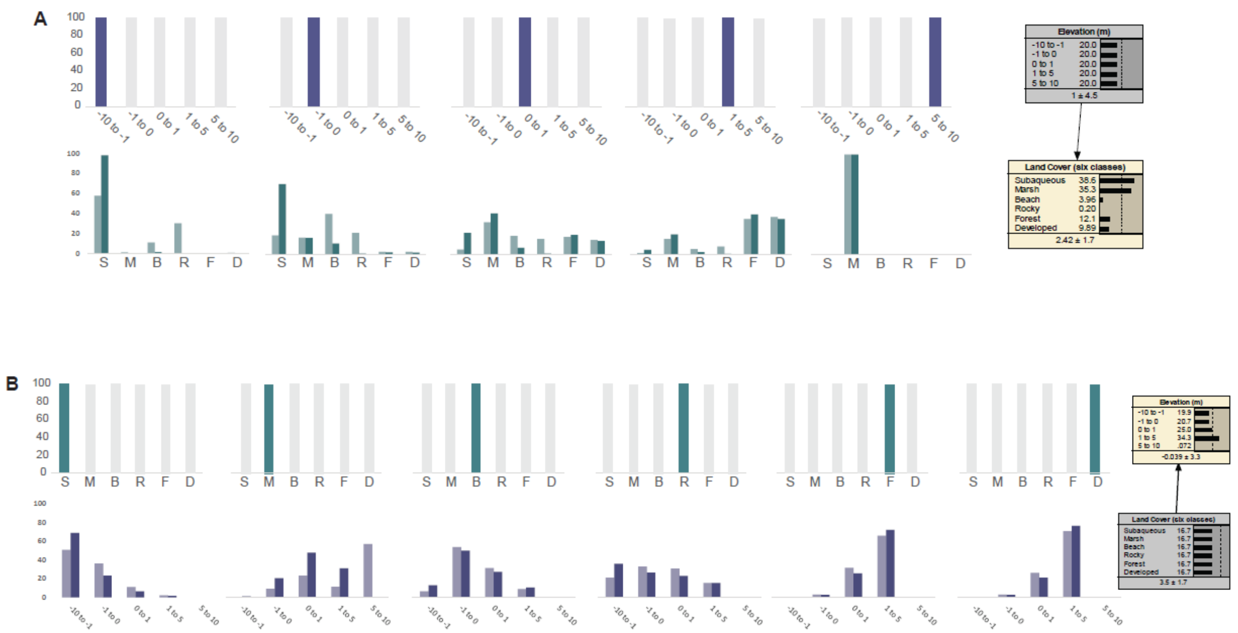

Figure 1. Updated probability distributions after training between elevation and land cover datasets with non-uniform (dark) and uniform (light) priors (the latter to limit regional LC bias), a) showing land cover distributions under selected elevation ranges and b) showing elevation distributions under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

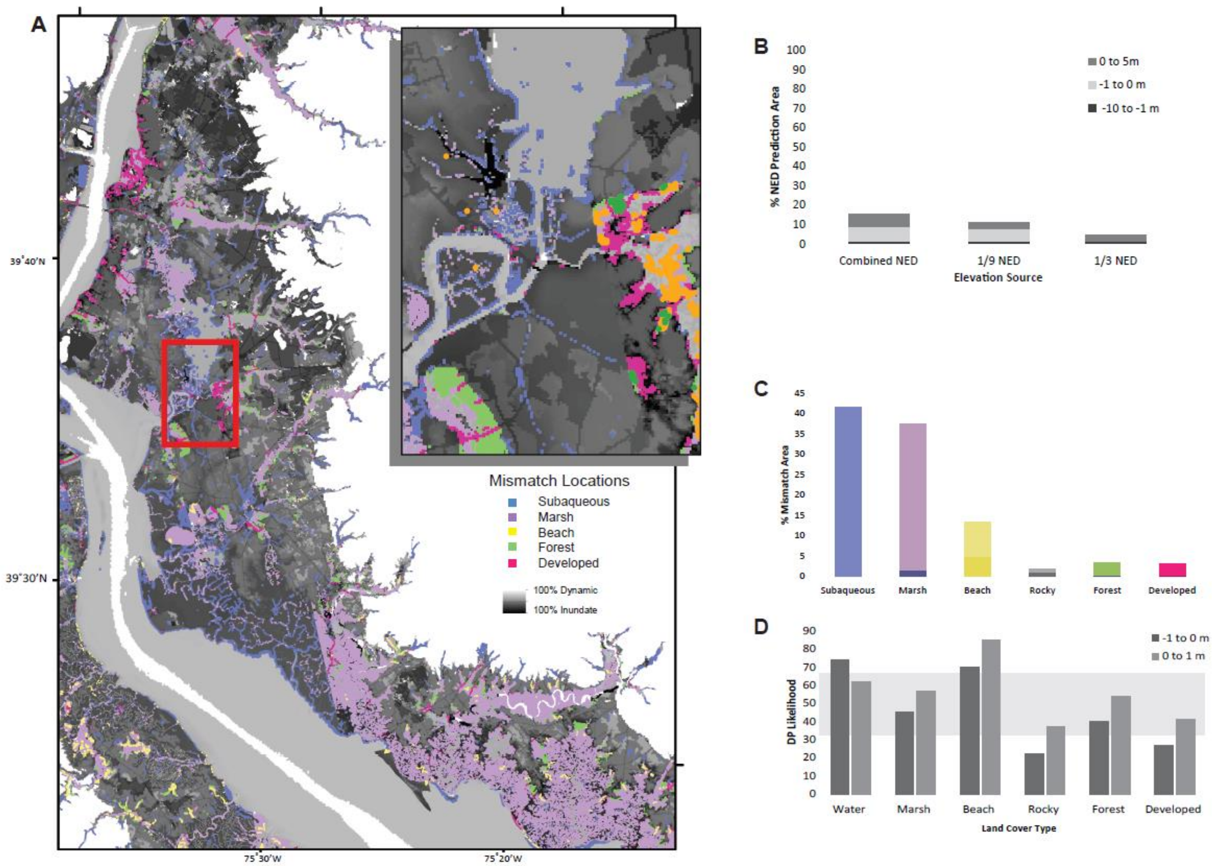

Figure 2. Results of mismatch analysis a) in selected area with inset of enlarged view; b) shown as percentage of the prediction area within the 1/3 National Elevation Dataset (NED) contour boundary and by elevation source type; c) by land cover type as a percentage of the total mismatch area, where 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).