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Evaluation of dynamic coastal response to sea-level rise modifies inundation likelihood

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Sea-level rise (SLR) poses a range of threats to natural and built environments[1,2], making assessments of SLR-induced hazards essential for informed decision making[3]. We develop a probabilistic model that evaluates the likelihood that an area will inundate (flood) or dynamically respond (adapt) to SLR. The broad-area applicability of the approach is demonstrated by producing 30 × 30 m resolution predictions for more than 38,000 km² of diverse coastal landscape in the northeastern United States. Probabilistic SLR projections, coastal elevation and vertical land movement are used to estimate likely future inundation levels. Then, conditioned on future inundation levels and the current land-cover type, we evaluate the likelihood of dynamic response versus inundation. We find that nearly 70% of this coastal landscape has some capacity to respond dynamically to SLR, and we show that inundation models over-predict land likely to submerge. This approach is well suited to guiding coastal resource management decisions that weigh future SLR impacts and uncertainty against ecological targets and economic constraints.

Future impacts from climate change, and particularly SLR[4], are expected to be widespread in coastal areas[2]. The northeastern US coastal landscape encompasses a variety of environments that will respond differently to SLR according to their geomorphology, geologic setting, ecology and level of development. Elevated water levels due to SLR will exacerbate coastal erosion and flooding[1,5], particularly along developed coasts that have substantial, fixed, low-elevation infrastructure and real estate[2]. Coastal habitats provide breeding areas and migration corridors for many threatened or endangered species[6]. Thus, a significant management challenge for densely populated areas such as the northeastern US, is to ensure the regional persistence of species, habitats and ecosystems that are vulnerable to SLR. Knowing where available coastal habitats are likely to be resilient, transition to a new state, or require a buffer zone to accommodate landward translation is essential for developing management and resource allocation strategies that preserve the intrinsic values of the coastal system[7].

The potential for both inundation and dynamic response exists for many coastal landscapes; however, SLR assessments typically focus on only one type of response. Inundation assessments flood existing topography with a projected sea level[3]. Although inundation seems straightforward to evaluate in terms of vertical and horizontal extent, its rigorous application requires accounting for technical and data uncertainties[8] as well as SLR uncertainties[9]. More importantly, this approach fails to include the dynamic response—due to anthropogenic, ecologic[10], or morphologic processes such as erosion and deposition—that drives coastal landscape evolution[11]. Dynamic response assessments[11,12] tend to represent cross-shore sediment transport processes explicitly with highly parameterized models, and can be used to make probabilistic assessments[13] by means of Monte Carlo methods and sensitivity analyses to communicate uncertainty[14]. Uncertainty affecting these approaches includes unknowns regarding rates and magnitudes of SLR, storminess, model parameter values, and the extrapolation from cross-shore profiles to spatially extensive domains. This uncertainty must be estimated by means of comparison with detailed observations.

As an alternative, we developed a data-driven coastal response (CR) model that considers both inundation and dynamic response using a range of SLR scenarios and data sets describing elevation and vertical land movement. We integrate these elements with land-cover information to assess CR likelihoods in the form of a dynamic probability, DP = 1-P(inundate), using a Bayesian network (Fig. 1). The modelling approach considers over 400 different combinations of input and output variables and incorporates their corresponding uncertainties, allowing distinctions between locations and environment types where current data and knowledge yield high-confidence predictions and where new information or better data are needed to resolve uncertain outcomes. The assessment covers coastal Maine through Virginia, and includes a region with a wide range of coastal development, infrastructure and environments found globally; including uplands, barrier beaches, spits, islands, mainland beaches, cliffs, rocky headlands, estuaries and wetlands. The study area is defined by the −10 and +10 m elevation contours and mapped as a 30 m grid.

To predict CR likelihoods (Fig. 2), we first compute an adjusted land elevation with respect to projected sea levels:

$$\mathrm{AE} = \mathrm{E} - \mathrm{SL} + \mathrm{VLM} + \mathrm{uncertainties} \qquad (1)$$

where AE represents the adjusted elevation with respect to a future sea level; E denotes the initial land elevation; SL is a projected sea level in the 2020s, 2030s, 2050s, or 2080s; and VLM gives the current rate of vertical land movement due to glacial isostatic adjustment, tectonics and other non-climatic effects such as groundwater withdrawal and sediment compaction[15]. Sources of uncertainty in AE predictions include SLR projections, elevation data accuracy, vertical datum adjustments, and the interpolation of VLM rates from point data; these geospatially explicit input uncertainties are propagated through the model to produce a probability mass function P(AE) for every grid cell (Fig. 2c,d). Once generated, AEs

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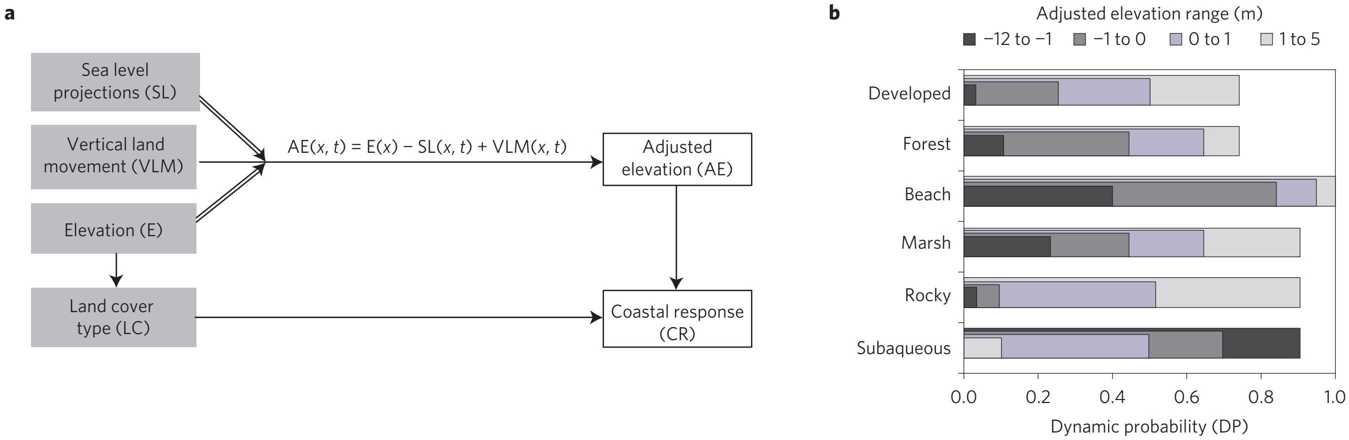

Figure 1 | Conceptual model and dynamic probability assignments. a, Schematic diagram showing the Bayesian network coastal response model, where x indicates dependence on the geospatial location and t indicates dependence on time. **b**, Coastal response assignments presented as dynamic probability (DP) based on adjusted elevation range and land-cover type; inundation probability is 1 − DP. For example, if adjusted elevation is in the range 0 to 1, the probability that a marsh environment will respond dynamically is 0.65.

are related through evaluation of their dynamic response potential with generalized land-cover information and used to produce a CR likelihood (Figs 1 and 2).

Discretized AE predictions provide an estimated submergence level comparable to many existing inundation models[3,16] (Fig. 2). However, our predictions include several notable improvements over existing approaches: SLR projections are associated with time, provided as a series of probabilistic decadal estimates aligning with planning and management time frames; we include VLM, ensuring relative SLR change is captured; and our probabilistic AE predictions include robust uncertainty assessments. Despite these differences, it is possible to compare these results with inundation models[3,16] as an initial test of consistency (Fig. 2a). Because we are forecasting sea levels for which observations do not exist, this initial test provides context for interpreting the subsequent CR predictions.

CR predictions augment inundation predictions by showing where dynamic response due to ecologic or morphologic processes is likely under a range of SLR scenarios (Figs 1 and 2b). DP is high in areas likely to preserve their current land-cover state or transition to another non-submerged state by adapting to SLR. Inundation occurs in areas unlikely to adapt in these ways. For example, an upland environment may persist with SLR and remain upland, or transition to a marsh; a marsh may vertically accrete to maintain itself, migrate laterally, or fail to keep pace with SLR and become inundated[10,17].

CR thresholds for specific land-cover types—based on a synthesis of published studies on SLR-induced change[10,17–19]—were used where available to define persistence and determine a DP (Fig. 1b). Where such information was unavailable, we assigned DPs to the remaining categories, following existing approaches used to fill information gaps with expert knowledge[20,21]. The potential for lateral translation of some environment types (marshes, forests and beaches) is not directly incorporated into our model; however, the co-occurrence of increasing DP and increasing elevation tends to capture this behaviour (Fig. 1b). Probability assignments and how they relate to SLR thresholds are presented in the Supplementary Information[22].

The DP assignments in this study (Fig. 1b) show that knowledge of particular outcomes is strongly related to elevation, and better understood for some land-cover types (such as beaches) than for others (for example, developed and forest). Elevation is an important first-order determinant of the spatial distribution of land-cover type (for example, salt marshes occur at low elevations; forests occur at higher elevations), and land-cover types in endmember elevation ranges are more likely to maintain their predicted response type through time, indicated by high (>0.75) or low (<0.4) DP values. For example, areas with AEs that exceed projected SLR are expected to remain dry and maintain their current land-cover type through dynamic response, whereas areas already submerged are anticipated to become even more inundated, regardless of land-cover type. At moderate AEs, a number of physical-process components not addressed by the model (for example, beach sediment supply; marsh accretion rate; human landscape modification) and land-cover-specific AE thresholds make CR predictions highly uncertain (for example, DP ∼ 0.5, Fig. 1). Thus, developed areas close to sea level, or beach areas that have an AE of −1 m have similar uncertainties in CR. Our approach allows any of these probability estimates to be updated as knowledge of coastal responses improves.

Comparison of AE and CR predictions for two time periods demonstrates the impact of changing SL on uncertainties (Fig. 3). Initially, nearly 70% of the region has potential for dynamic response[22] (Fig. 3), suggesting that for the majority of the northeastern US an inundation approach does not adequately describe the SLR response. A highly dynamic location, such as Prime Hook National Wildlife Refuge (Fig. 3a), shows 70% of the area is predicted to be submerged in 2020 (that is, AE < 0), although the CR shows only 2% of the area is likely to inundate (DP < 0.5). The difference comes from the predicted dynamic response of the marsh, and demonstrates the importance of including this information to depict more realistic SLR effects on the landscape. As expected, there is a trend towards increased submergence (AE < 0) and greater prediction uncertainty through time for both AE and CR. This behaviour is largely attributable to the SLR projections and their associated uncertainties; 2080s sea-level projections are the highest and the most uncertain, which are in turn reflected in wider probability distributions for predicted outcomes (Fig. 3b).

SLR projections and associated uncertainties have the greatest effects on land at moderate initial elevations (−1 to 0 m and 0 to 1 m). For each land-cover type, we can identify when our knowledge of the CR is most uncertain (that is, DP = 0.5) and when we are likely to observe a transition from dynamic response to inundation, indicating a SLR threshold has been exceeded (Fig. 4). Here we relate our numerical CR predictions to verbal equivalents following the Intergovernmental Panel on Climate Change Fifth Assessment Report[23]. At elevations of −1 to 0 m, developed areas are likely (66–100% probability) to inundate before the 2020s (relative to

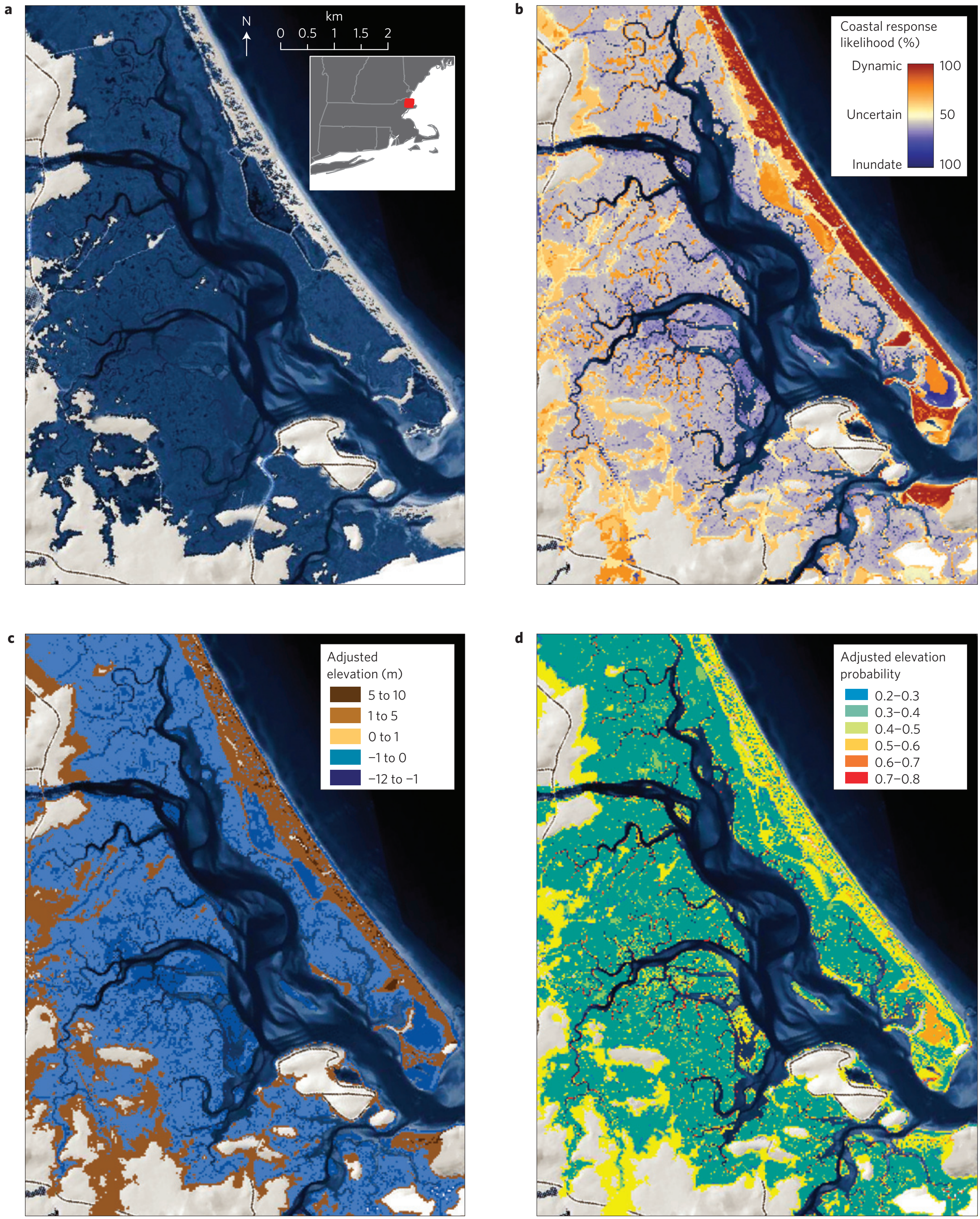

Figure 2 | Comparison of predicted outcomes for Plum Island, Massachusetts. a, Surging Seas inundation map under 1.5 m of SLR. **b**, Predicted coastal response likelihoods for 2080s sea-level scenario (comparable projected SL to **a**). **c**, Most probable 2080s adjusted elevation (AE, or inundation levels). **d**, Probabilities of the AE values in **c**. Maps reproduced with permission from B. Strauss at Climate Central's Surging Seas project (http://ss2.climatecentral.org/#13/42.7573/-70.8059?show=satellite&level=4&pois=show).

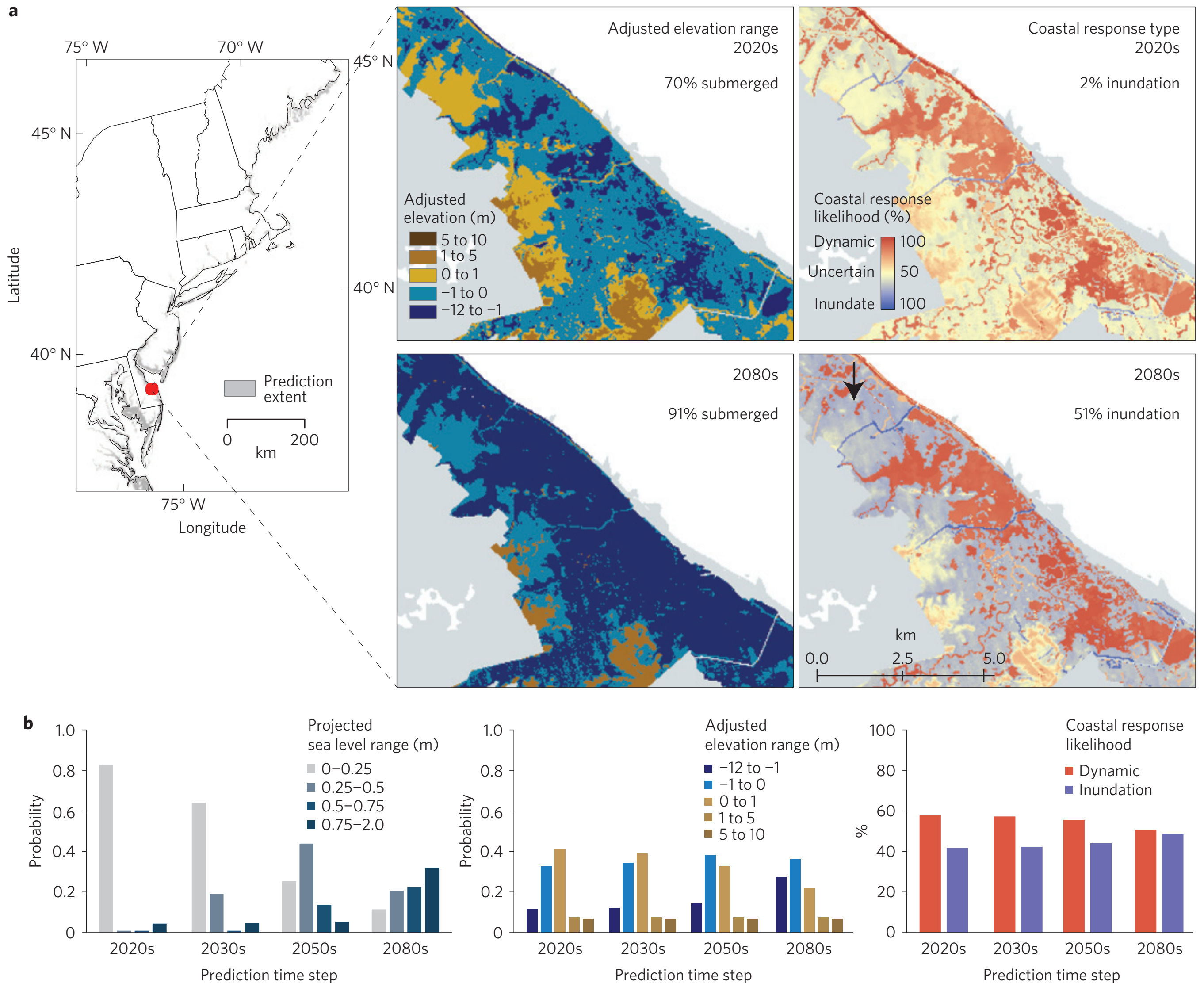

Figure 3 | Spatiotemporal changes in probability distributions at Prime Hook National Wildlife Refuge, Delaware. a, Regional map showing the spatial extent of predictions (grey shading) and examples of adjusted elevation and coastal response predictions for the 2020s and 2080s. **b**, Modelled probability distributions for projected sea level, adjusted elevation and coastal response for each time step at a single cell location (black arrow in the lower right panel of **a** indicates the location).

the base period of 2010), and marshes and forests after the 2030s. In the 0–1 m range, inundation is likely for developed areas by the 2050s, and marshes and forests by the 2080s. At any time step, rocky areas are likely to inundate, whereas beaches are likely to very likely (90–100% probability) to respond dynamically. Subaqueous environments are likely to be dynamic at any elevation range and time, as they are expected to maintain their initial land-cover state; however, those found below mean high water (MHW) have a greater DP than inland water bodies above MHW (Fig. 4), presumably because they are responding to changes in sediment transport and resuspension, waves, tides and other factors.

Model predictions provide a broad view of the coastal response to SLR and other processes at resolutions commensurate with landscape-scale decision-support needs. The different scenarios depict potential landscape changes that can be used to quantify uncertainties, define a planning horizon, or improve an understanding of risk tolerance[14]. This information can guide decisions regarding land use and management, and provides context needed for understanding tradeoffs that may be necessary to achieve management goals, such as future land acquisitions or identification of land area buffers for ecosystem migration. Furthermore, the approach presented here is sufficiently generic to apply at other coastal locations globally where environments are similar but data may be more limited in availability or resolution. Probabilistic outcomes can help prioritize where future research efforts are directed to improve forecast capability, and as knowledge improves—for example, owing to better understanding of ice sheet behaviour[24], storminess[25], adaptation actions[1], or more detailed morphologic and ecologic process information[2]—the model and predictions can be updated.

Understanding which response—inundation or dynamic—best describes the future system state over broad coastal landscapes can inform appropriate selection of more detailed modelling approaches. In some locations, submergence may be the most pressing problem, and properly applied inundation models can adequately depict future conditions. Where complex coastal processes affect the landscape, detailed morphological models[11–13]

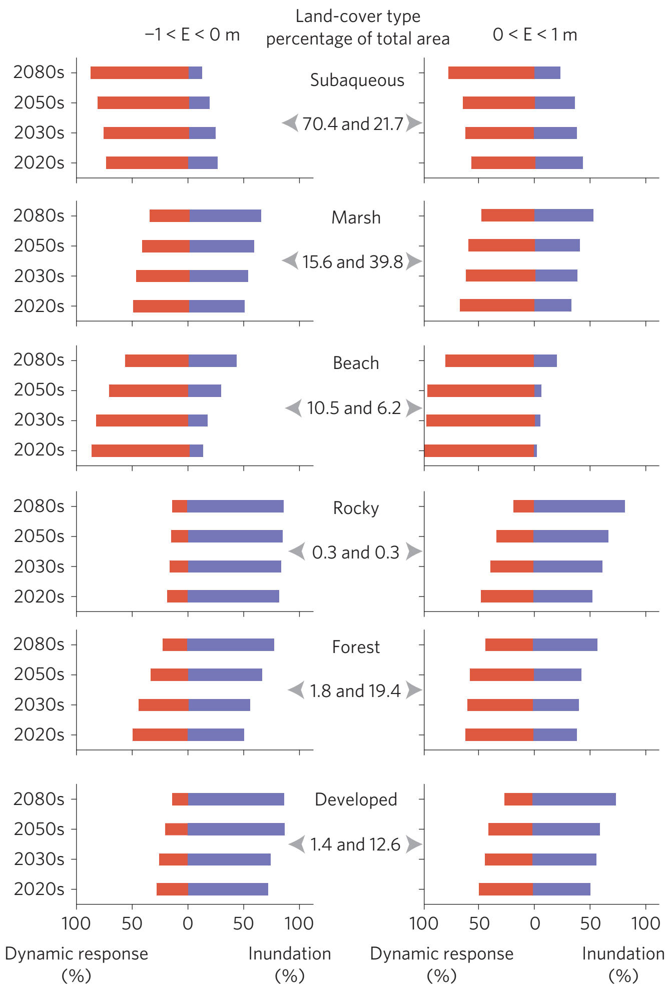

Figure 4 | Plots showing shifting coastal response likelihoods for each land-cover type through time conditioned on moderate initial (present day) elevations. Central column shows the total percentage of the prediction area comprised by each land-cover type by each elevation (E) range. Red shows the probability of a dynamic response and blue shows the probability of inundation.

may be best suited to explore future scenarios. Our modelling framework demonstrates comprehensive consideration of both response types is possible through an approach that can be applied to a variety of coastal settings, over a given time frame, or amount of SLR.

Methods

Methods and any associated references are available in the online version of the paper.

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Author contributions

E.R.T. and N.G.P. developed the concept; E.E.L., N.G.P. and E.R.T. conceptualized and designed the model; N.G.P. built the model; E.E.L. and S.R.S. performed the model runs; E.E.L. assessed and analysed the data; R.M.H. contributed the SLR projections; D.B.J. contributed regional elevation data; E.E.L., E.R.T. and N.G.P. co-wrote the paper with input from all co-authors.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to E.E.L.

Competing financial interests

The authors declare no competing financial interests.

Methods

Our model uses a Bayesian network (BN), which we exploit here for its ability to propagate uncertainty, perform inference and calculate conditional probabilities, and structure the integration of stochastic, deterministic and expert relationships. BNs have been applied to a variety of coastal problems[6,26,27] and output results in a probabilistic form well suited to address decision-support needs. The relationships between parameters in a BN are established through directed links (causal relationships, Fig. 1) which represent conditional probabilities trained on observations, probabilistic or deterministic equations, or expert opinion. An advantage in using BNs is their robust consideration of uncertainty. Uncertainties in the relationships derived from the observational training and uncertainties in the input parameters are propagated through the BN to provide a predicted probability for each discrete outcome. The training captured the co-occurrence of land-cover and elevation inputs, used explicit relationships and input uncertainties among parameters as defined by equation (1), and assigned dynamic response probabilities (DP) to a conditional probability table (CPT) based on knowledge specific to each scenario of land cover (LC) and adjusted elevation[22] (AE) to generate a coastal response (CR) prediction.

Our BN stores conditional probabilities to make predictions using combinations of statistical inference and joint probability calculations. For AE we use

$$P(\mathrm{AE}_i) = \sum_{\mathrm{E,SL,VLM,LC}} P(\mathrm{AE}_i|\mathrm{E,SL,VLM})\, P(\mathrm{E}|\mathrm{LC})\, P(\mathrm{SL}_j)\, P(\mathrm{VLM}_j)\, P(\mathrm{LC}_j) \quad (2)$$

where we evaluate the ith AE outcome from five discrete possibilities; the summation accounts for uncertainties in the input variables; the first term on the right is the probabilistic relationship for equation (1) conditioned on inputs from the jth spatial location at a particular time; and the second term accounts for the relationship between LC and elevation, which is updated using Bayes theorem[22]

$$P(\mathrm{E}_i|\mathrm{LC}_j) = P(\mathrm{LC}_j|\mathrm{E}_i) \times P(\mathrm{E}_i)/P(\mathrm{LC}_j) \quad (3)$$

The remaining (independent) terms in equation (2) are updated with input from data or model sources, and are, in general, uncertain. The only exception is LC, which is entered as if known with certainty for each grid cell, as uncertainty for this term is unquantified[22]. As noted in this paper, there is an inherent correlation between current elevation and LC; capturing this relationship through inference training (Bayes' rule) allows us to use LC information to update the prior elevation information (based on the values of the digital elevation model [DEM] over the entire domain) and constrain elevation uncertainties attributed to errors in the DEM. For CR, we have

$$P(\mathrm{CR}_i) = \sum_{\mathrm{AE,LC}} P(\mathrm{CR}_i|\mathrm{LC,\ AE})\, P(\mathrm{AE}|\mathrm{LC})\, P(\mathrm{LC}_j) \quad (4)$$

where $P(\mathrm{AE})$ is computed from (2) (and depends on SL, VLM, E, as well as LC) and $P(\mathrm{CR}_i|\mathrm{LC, AE})$ are determined from published work or expert knowledge[10,17–19]. In our implementation, LC is exact as noted above and so the summation is performed only over the AE values—but using the BN allows for uncertainty in LC and we would apply this capability if the land-cover maps included uncertainty.

Regional SLR projections were generated using multiple sources including scenarios—Representative Concentration Pathways (RCPs)—in the 2014 Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5; ref. 28). A three-component approach[29] for the SLR projections included an ocean term (including thermal expansion and local ocean height), ice melt and land water storage. The ocean term is taken from 24 Coupled Model Intercomparison Project 5 (CMIP5) models[30] (http://cmip-pcmdi.llnl.gov/cmip5/data_portal.html); whereas the first part is global, the second is computed on a 1° × 1° grid and extracted at the nearest ocean grid cell to each grid point in our domain. Ice melt was estimated for the Greenland Ice Sheet and the two Antarctic Ice sheets[20], and the glaciers and ice caps[31,32]. Land water storage was based on IPCC AR5 WG1 (ref. 4). Set percentiles (10th, 25th–75th, and 90th) were estimated for each of the three components of sea-level change. These projection ranges are representative of key uncertainties in the components of sea-level rise.

SLR projections at each time interval (2020s, 2030s, 2050s, or 2080s) were initialized with uniformly distributed prior probabilities and updated with the regional projection probabilities (Fig. 3b). Vertical land movement rates were estimated from GPS data[33] and tide station records[34]. The highest-resolution elevation data available (either ~3 m or ~10 m horizontal resolution; ±43 cm or 1.25 m vertical) through the National Elevation Dataset (NED; ref. 35) were vertically adjusted to the MHW datum; bathymetry data at coarser resolution (~30 m) from the Coastal Relief Model were used in areas of open water. To represent coastal landscape types, we generalized regional land-cover data into six categories based on established differences in physical and biological processes that drive responses to SLR (ref. 22).

Results span the coastal zone from initial elevations of 10 m inland to −12 m offshore. A comprehensive discussion of methods and input data sets can be found in the Supplementary Information[22].

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