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ORIGINAL PAPER

High uncertainty over the future of tidal marsh birds under current sea-level rise projections

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Abstract
Sea-level rise (SLR) is projected to increase dramatically with profound effects on tidal marshes, yet uncertainty stemming from underlying climate change scenarios, model specifications, and temporal scale is a major hurdle to conservation planning. We compared likely effects of SLR for 2030 and 2050 under static inundation and dynamic response model predictions for the northeastern USA, where tidal marshes experience elevated rates of SLR compared to global averages. Static inundation and dynamic response models of SLR, which differ in how they incorporate uncertainty associated with local processes and biophysical feedbacks, have historically been applied at different scales, and generally differ in spatial and temporal predictions of marsh vulnerability. We used population estimates for five tidal marsh bird species of conservation concern to predict patterns of population change for each SLR model and examined how uncertainty affects planning decisions for these species. Static inundation and dynamic response models differed markedly in their predictions for 2030, yet both models predicted with reasonable certainty that only 10–15% of tidal marsh in northeastern USA is likely (> 66% chance; as defined by the IPCC) to remain by 2050. Most (85–90%) of the marsh is predicted to be as likely as not (33–66% chance) to disappear, representing high potential for the loss of habitat for > 85% of current populations of four of the five bird species. We propose a planning approach using guidelines established by the IPCC to categorize uncertainty associated with marsh loss due to SLR and apply it to prioritize key sites for preservation.

Keywords Avian · Climate change · Conservation planning · North America · Salt marsh · Sea-level rise

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Introduction

Although the consequences of climate change are broadly understood, there is much uncertainty as to how conditions will change. This uncertainty represents a major challenge to the development of effective adaptation strategies, particularly at regional scales where coordinating effort across agencies and management boundaries is necessary for the preservation of species. Conservation planning to support long-term management targets, for example, would ideally prioritize not only land that is important now, but also land that will remain or become important in the future (e.g., Carroll et al. 2010; Veloz et al. 2013; Zhu et al. 2015). Translating this uncertainty to practical planning decisions is an ongoing challenge for conservation during rapid climate change. Incorporating an approach to quantify uncertainty that is derived probabilistically from model results, coupled with consistent terminology based on the likelihood of the outcome, such as that recommended by the Intergovernmental Panel on Climate Change (IPCC; Mastrandrea et al. 2011) can begin to address these challenges..

Coastal environments cover only 9% of the Earth's land surface yet support over 25% of the human population (Kummu et al. 2016). By sequestering carbon, filtering sediment and pollutants, buffering against storms, supporting fisheries, and providing recreational opportunities (Gedan et al. 2009), coastal environments are among the most economically important yet vulnerable ecosystems (Barbier et al. 2011; Arkema et al. 2013). Despite their importance, at least 25% of the world's coastal wetlands have been lost through conversion for human use (Mcleod et al. 2011) and much of the remaining area is vulnerable to sea-level rise (SLR). Tidal marshes in particular, are dynamic coastal ecosystems that are already vulnerable due to their frequent proximity to human development, and their persistence in the face of SLR depends on a suite of biological and physical processes (French 2006; Kirwan and Murray 2007). Historically, these marshes have avoided inundation or transition to either open water or mud flats by building vertically at rates similar to, or exceeding SLR (Cahoon et al. 2006; French 2006) or by migrating inland (Smith 2013). Historical responses to SLR are an imperfect model for the future, however, because factors such as climate, water quality, sediment delivery rates, primary productivity, and space for marsh migration continue to change with human activity (Parris et al. 2012; Kirwan and Megonigal 2013).

Eastern North America contains over one-third of the world's tidal marsh, which support a number of vertebrate endemics (Greenberg and Maldonado 2006), and provide many additional species, particularly birds, with important habitat throughout the year (Correll et al. 2016). SLR is projected to increase dramatically with profound effects on tidal marshes, yet uncertainty regarding the magnitude (McGranahan et al. 2007; Nicholls and Cazenave 2010; Sallenger et al. 2012; Kirwan and Megonigal 2013; Kopp et al. 2014; Sweet et al. 2017a, b)—due to differences between carbon emissions scenarios (e.g. representative concentration pathways, RCP; van Vuuren et al. 2011), differences in model assumptions (e.g., static vs. dynamic process-based models; Hawkins and Sutton 2009; Kirwan et al. 2016), and a variety of oceanic and atmospheric dynamics (e.g. Sweet et al. 2017b and references therein)—is a major hurdle to conservation planning and the development of effective adaptation strategies (Nicholls and Cazenave 2010).

Static inundation or 'bathtub' models have dominated larger-scale assessments of marsh vulnerability (e.g. Nicholls 2004; Cooper et al. 2008) as they can be developed rapidly and inexpensively with relatively few data sources (i.e., elevation, proximity to shoreline, and SLR predictions). Static models hold coastal topography constant as sea level increases and potentially inundated areas can be identified for a range of SLR predictions to assess vulnerability and potential impacts (Mcleod et al. 2010). Static models generally assume that marshes do not respond to increased rates of SLR through biophysical feedback that accelerates soil building, or through landward marsh migration. Most static models predict significant or catastrophic marsh losses this century (e.g., Cooper et al. 2008; Craft et al. 2009), but there are concerns that they underestimate marsh resilience (e.g., Kirwan et al. 2016). Dynamic models generally have been restricted to smaller spatial scales because they incorporate biophysical feedbacks that may strongly depend on local conditions (Passeri et al. 2015) and require data derived from field measurements (e.g., Morris et al. 2002; Kirwan and Guntenspergen 2010; but see Schuerch et al. 2018 for a global example). Dynamic models generally predict smaller marsh losses than static models but may overestimate marsh resilience to SLR because they often do not fully consider cumulative effects of historical subsurface processes (Parkinson et al. 2017). Despite these well described differences, we know little about how uncertainty and differences between static and dynamic models may influence the prioritization of areas for conservation. A common way to assess the risks associated with SLR is to generate a suite of plausible scenarios that incorporate a range of possible futures based on different SLR scenarios (Moss et al. 2010; Parris et al. 2012). This approach, however, may fail to provide sufficient guidance for managers and policy makers because the likelihood of each scenario is unknown (Kerr 2011), and is further complicated by the fact that comparisons between dynamic and static responses are lacking.

We addressed this guidance issue using existing static and dynamic models, developed under multiple emissions scenarios, to evaluate potential effects of SLR on key conservation targets in tidal marshes of the northeastern USA. We determined the temporal and spatial patterns of future habitat loss for five high priority avian conservation targets, inferred the resulting potential for population change, and examined how uncertainty affects the practical planning decisions that should be made for these species. We used our results to identify and prioritize key sites for preservation and to recommend how uncertainty (explicitly quantified as a probabilistic estimate of an outcome) in the loss or dynamic response of tidal marshes to SLR can be integrated into planning decision.

Methods

We used an existing probabilistic modeling framework designed by Lentz et al. (2015) to explore varying SLR impacts across the region (https://woodshole.er.usgs.gov/project-pages/coastal_response/data.html) on the area of 8405 saltmarsh patches in the northeastern USA (Fig. 1). Saltmarsh patches between Maine and Virginia were defined by creating a 50 meter buffer around all Estuarine Intertidal Emergent Wetland polygons (Cowardin et al. 1979) identified in the National Wetlands Inventory (USFWS 2010) following Wiest et al. (2016). Polygons with buffers that intersected were merged, as distances ≤ 100 meters between saltmarsh habitats were not perceived as a barrier to movement based on estimates of home range size and habitat use for Nelson's (*Ammospiza nelsoni*) and saltmarsh (*A. caudacuta*) sparrows (Shriver et al. 2010), two priority species for saltmarsh conservation in the region.

The probabilistic modeling framework of Lentz et al. (2015) was developed for a sea-level-rise decision-support model that considers two coastal response types—a static response that is driven by inundation and a response that also considers dynamic evolution

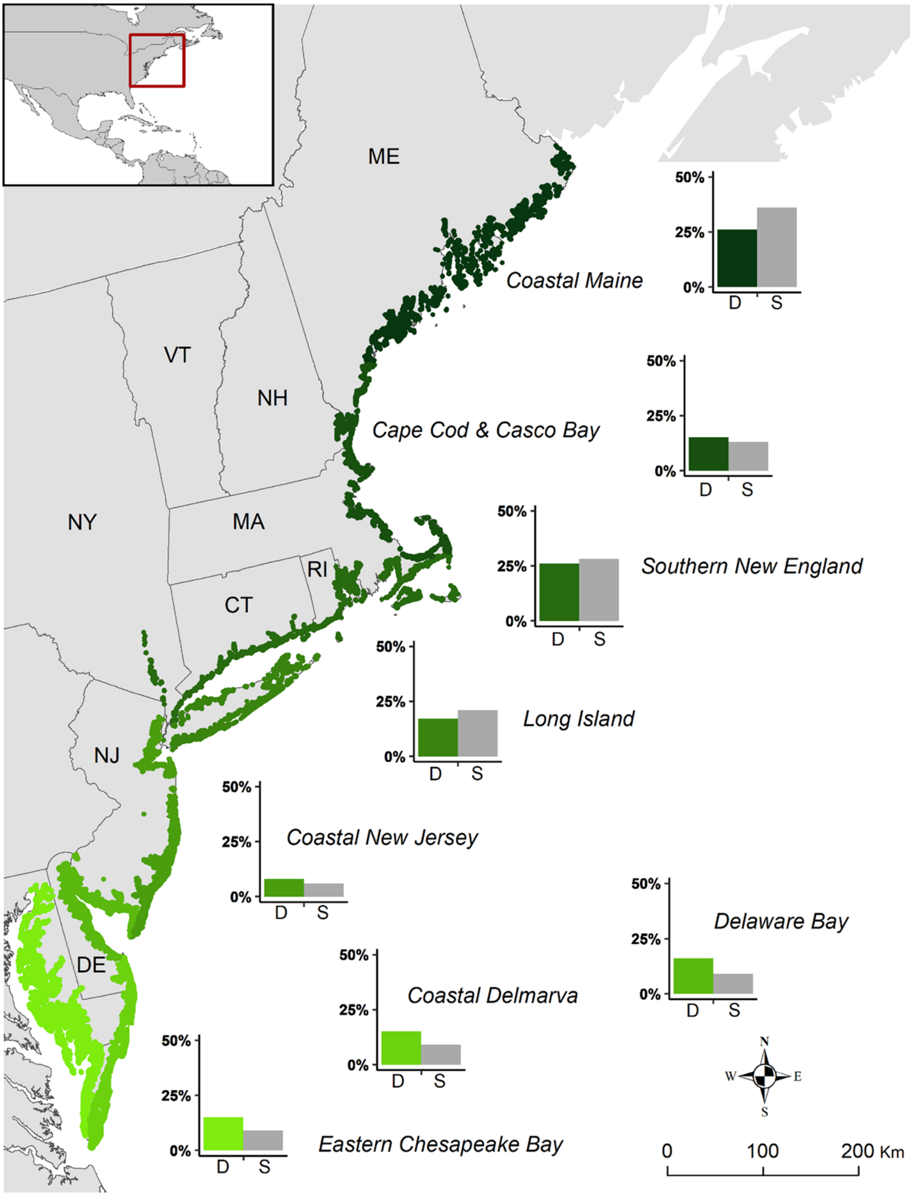

Fig. 1 A comparison of tidal marsh area predicted to survive sea level rise from dynamic (D; green bars) and static (S; gray bars) models. Bars represent the percent of 2010 tidal marsh area in each of 8 sub-regions in northeastern North America (after Wiest et al. 2016) predicted to be likely or very likely (> 66% chance) to adapt to SLR and avoid inundation (dynamic model) or to remain above sea level (static model) in 2050. Location of study area in North America indicated by box on map in top left corner

of the coastal landscape. The static and dynamic response layers of this framework rely on a Bayesian network to predict land elevation with respect to projected mean high water in 2030 and 2050 based on relative SLR estimates from the IPCC's RCP scenarios 4.5

and 8.5 (Stocker et al. 2013). Estimates of SLR are coupled with vertical land movement rates due to glacial isostatic adjustment, tectonics, and other non-climatic effects such as groundwater withdrawal and sediment compaction, and current elevation data (Lentz et al. 2015). The resulting SLR response layers differ from many static inundation models by integrating uncertainty of inputs across a given decade, and including several RCP scenarios rather than developing separate estimates for each scenario. In the Lentz et al. (2015) model, predicted adjusted elevations are discretized into five elevation ranges (− 10 to − 1, − 1 to 0, 0 to 1, 1 to 5, and 5 to 10 m) and the probability associated with the predicted elevation at each location is provided as a separate layer to quantify uncertainty. A third data layer describes the likelihood that the dynamic response of the coastal landscape will be sufficient to avoid inundation at a given level of SLR. This last portion of the model used a combination of published research and expert elicitation to identify SLR thresholds for land conversion for six land cover types (subaqueous, marsh, beach, rocky, forest, and developed) within each elevational range and time period (Lentz et al. 2015 and references therein). For land classified as marsh, the likelihood of a dynamic response refers to the possibility that sea-level rise rate, suspended-sediment concentrations, vertical accretion rate, and (or) tidal range in an area can allow marshes to persist in light of predicted water-level increases.

For our analysis, we reclassified the adjusted elevation layers (hereafter 'static layers') for 2030 and 2050 from the initial five elevation ranges into a binary raster in which pixels are predicted to be above or below sea level (given no dynamic response). We also reclassified the dynamic probability layers (hereafter 'dynamic layers') for 2030 and 2050 from the continuous probability of avoiding inundation given by Lentz et al. (2015) into categories that match the standard terminology used to refer to likelihoods by the IPCC (Mastrandrea et al. 2011). Using the IPCC's uncertainty terminology, where "unlikely" implies a < 33% chance of dynamically responding (or avoiding inundation), "as likely as not" a 33–66% chance, "likely" a 66–90% chance, and "very likely" a > 90% chance, enables communication and decision-making to be based on calibrated language in which clear categories have been identified and risks can be evaluated.

We extracted estimates of adjusted elevation and likelihood of a dynamic response to sea level rise by 2030 and 2050 using the "extract by mask" tool in ArcGIS 10.4 (ESRI 2016) with the layer of 8405 saltmarsh patches (Wiest et al. 2016) as a mask. This procedure provided static and dynamic inundation predictions for areas corresponding to 8129 (97%) saltmarsh patches. We classified the remaining 276 patches (< 0.08% of the original saltmarsh area) that lacked clear relationships to data in the SLR layers due to differences in land cover classifications between models, as having insufficient data.

For each layer, we estimated the percent of tidal marsh remaining by 2030 and 2050 using two approaches that differ in how they address the potential loss of information when using irregularly shaped polygons to extract data from a raster comprising square pixels. First, we assumed that the pixel values extracted from the raster layers were representative of the polygon as a whole. For each raster, we multiplied the proportion of pixels in each class by the original area of the saltmarsh patch. For the static model, this resulted in an estimate of the area of tidal marsh expected to be submerged or remain unflooded tidal marsh. For the dynamic model, we obtained an estimate of the area of each patch with a given chance of avoiding inundation based on the IPCC likelihood categories. Second, we used only the area of the pixels extracted by the mask to estimate the proportion of the entire area that is predicted to fall into a given category. Both approaches produced similar results (Supplementary Information; Table S1) and we present only those based on the first here.

For each layer and each decade, we quantified the potential effects of future SLR on the populations of five bird species—clapper rail (*Rallus crepitans*), eastern willet (*Tringa semipalmata semipalmata*), Acadian Nelson's sparrow (*Ammospiza nelsoni subvirgatus*), saltmarsh sparrow (*A. caudacuta*), and seaside sparrow (*A. maritima*). These populations are of particular conservation interest because they largely or entirely breed in tidal marshes. Population trajectories vary from annual declines of 9% or more and projected extinction within the next few decades, to current stability (Correll et al. 2017; Field et al. 2017a, b, 2018; Roberts et al. 2019). Population estimates for each of the five species were derived from a comprehensive regional marsh bird survey in 2011 and 2012 (Wiest et al. 2016). A Bayesian network model incorporated a suite of environmental covariates and survey results to estimate population density within 8405 saltmarsh patches throughout the region (Wiest et al. 2019). Density estimates indicated that clapper rails, eastern willets and seaside sparrows had population sizes > 100,000 in the northeastern USA, whereas saltmarsh (< 60,000) and Acadian Nelson's (< 7000) Sparrows had much lower population sizes in the region (Wiest et al. 2016, 2019). We predicted future population sizes for each species under the static model by multiplying the original density estimates for each patch by the proportion of the patch's original area that is expected to remain above sea level by a given year, and then summing across patches. To estimate change assuming dynamic responses to SLR, we prorated the original density estimates for each patch based on the proportion of the original patch area classified as falling within each IPCC likelihood category.

To inform current planning that prepares for climate change and uncertainty associated with marsh loss due to SLR, information about the full range of possible consequences and associated probabilities is needed to support a risk management perspective. Risk is a function of probability and consequence and often information on the tails of the distribution of outcomes can be especially important (Mastrandrea et al. 2011). Therefore, we combine results from static and dynamic layers to identify patches that cannot be relied upon to support conservation goals because they are predicted to be completely inundated in the static layer and are as likely as not, or unlikely (< 66% likelihood) to respond dynamically to sea level rise and avoid inundation by 2030 or 2050 (Supplementary Information, Tables S2, S3). We also identify patches that are predicted both to remain unflooded in the static layer and are likely or very likely (≥ 66% likelihood) to respond dynamically and avoid inundation by these dates (Supplementary Information, Tables S2, S3). These locations provide a starting point for conservation planning in the region because they have a high likelihood to have value in both the short- and long-term, and can then be prioritized to maximize representation of conservation benefits relative to costs.

Results

Regardless of whether we assume static inundation or a dynamic response to SLR, dramatic declines in the area of tidal marsh would not be surprising (Table 1). The static outcomes predicted almost half the salt marsh area in the northeastern USA is likely to be underwater by 2030 and ~90% is likely to be inundated by 2050 (Table 1). Uncertainty in the likelihood of a dynamic response of tidal marsh to SLR was high and differed little between 2030 and 2050. Although the fate of most marsh could not be predicted with high confidence, our best estimates suggest that only ~ 15% of the current area is likely or very likely to adapt to SLR and remain tidal marsh (Table 1).

Table 1 Percentage of northeastern North American tidal marsh present in 2010 that is predicted to remain above sea level (a.s.l.) with a static model or adapt to sea level rise (SLR) with a dynamic model in 2030 and 2050

Model	Predictions	2030 (%)	2050 (%)
Static			
	Elevation predicted to be greater than 0 meters a.s.l.	51.05	10.52
	Insufficient data	0.08	0.08
Dynamic			
	Unlikely to adapt to SLR increases (0–33%)	0.06	0.07
	As likely as not to adapt to SLR increases (33–66%)	84.88	85.34
	Likely to adapt to SLR increases (66–90%)	14.73	14.28
	Very likely to adapt to SLR increases (90–100%)	0.25	0.23
	Insufficient data	0.08	0.08

See methods for procedure used to estimate area and description of insufficient data. See Lentz et al. (2016) for a detailed description of the models

Substantial reductions in the population sizes of all five tidal marsh specialist birds are predicted, under both static and dynamic outcomes (Fig. 2). Four of the five species are projected to be at risk of losses of habitat that supports > 85% of their current populations under both scenarios, with Acadian Nelson's sparrow faring only slightly better. Outcomes differ slightly in the severity of predicted losses, with the dynamic responses showing somewhat more optimistic projections for all species except Acadian Nelson's

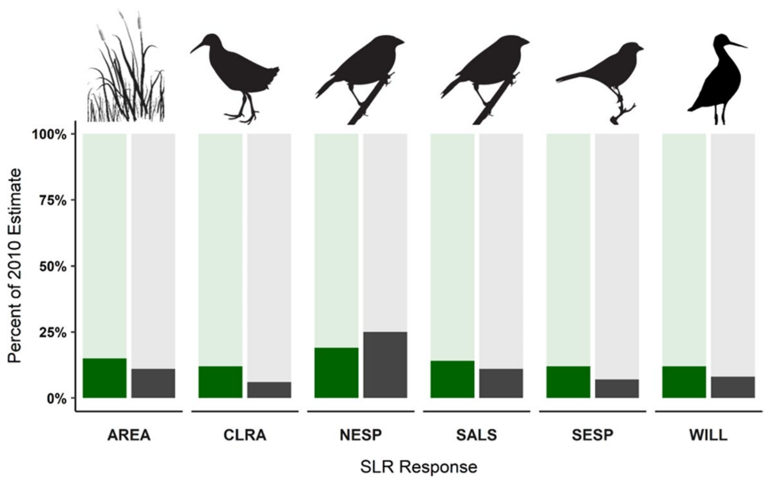

Fig. 2 Percent of 2010 tidal marsh area (AREA) and population estimates for 5 tidal marsh birds (CLRA: Clapper Rail; NESP: Acadian Nelson's Sparrow; SALS: Saltmarsh Sparrow; SESP: Seaside Sparrow; and WILL: Eastern Willet) predicted to be likely or very likely (> 66% chance) to adapt to SLR and avoid inundation (dynamic model, green) or to remain above sea level (static model, gray) in 2050. Bird silhouettes from www.allaboutbirds.org © Cornell Lab of Ornithology, used with permission. Marsh image from https://www.goodfreephotos.com

sparrow. Differences between static and dynamic predictions, however, are small, ranging from 2.7 to 6.0%.

Outcomes differed in the spatial distribution of tidal marsh predicted to be lost in the Northeast by 2050 (Fig. 1). In general, the dynamic response outcomes suggest that a greater proportion of tidal marshes from coastal New Jersey south to the Eastern Chesapeake Bay are likely to adapt than are predicted to remain by the static model. In contrast, dynamic response outcomes suggest that less marsh in coastal Maine, southern New England, and Long Island is likely to adapt than is predicted to remain under the static model, indicating that static inundation outcomes may overestimate the adaptability of tidal marshes in these areas. In all regions, however, both models project that only one-third to < 10% of the current area is likely to remain.

Discussion

SLR predictions are sensitive to underlying climate change scenarios, model specifications, and temporal scale (Hawkins and Sutton 2009; Stocker et al. 2013), all of which generate uncertainty in future projections. Potential changes, however, are sufficiently severe that it is important that we find ways to identify conservation and management decisions with a high chance of success across a range of future scenarios, despite uncertainty.

The use of standardized terminology to describe uncertainty is also expected to assist decision makers by eliminating confusion and identifying the level of risk associated with climate change outcomes. For this reason, we have followed IPCC guidelines in which a statement that an outcome is "likely" means that the probability of this outcome exceeds ≥ 66% probability. When a prediction falls within this range, it also implies that all alternative outcomes are "unlikely" (0–33% probability). Focusing on the upper and lower probabilities of an outcome when prioritizing conservation action does not suggest that outcomes with a 33–66% probability (as likely as not) are unimportant, but simply that they may be better suited for later stages of planning.

The static and dynamic models examined here differed markedly in their predictions for 2030, but both predicted that there is only 10–15% of current tidal marsh in the northeastern US that is likely to remain by 2050 (Lentz et al. 2016; Table 1). These projected marsh losses correspond to the disappearance of breeding habitat for over 75% of the current populations of each specialist marsh bird species, suggesting potential for severe impacts on those that currently have stable populations (e.g., willet) as well as those that are already considered globally endangered (e.g., saltmarsh sparrow).

In the face of potentially catastrophic losses of tidal marsh in the Northeastern USA, where availability of land to protect is limited and unpredictable (Field et al. 2017a, b), we need to account for the uncertainty associated with available conservation options. Our models suggest that, although there is much marsh that might persist, there is only about 15%, both regionally and within most sub-regions, that we can be confident will remain potential habitat for tidal marsh birds by 2050. Much of the remaining area may respond dynamically to SLR, however, it is just as likely that it will not. Notably, we found that less marsh in northern parts of the region is likely to respond dynamically and remain tidal marsh than is predicted to remain unflooded in the static model, while tidal marshes from coastal New Jersey south to the Eastern Chesapeake Bay are more likely to adapt and remain marsh habitat when compared to projections from the static model. The lack of consistent pattern throughout the Northeast may reflect sub-regional differences in sediment load, size of patches, slope of adjacent land cover types or tidal range, and will require additional investigation and consideration of local factors. Another consideration is the existing proportion of high marsh versus low marsh across the region and how changes in the relative proportions and composition of tidal marsh may affect rates of dynamic response to SLR. Given this situation, planning decisions require a precautionary approach with attention focused on protecting those areas most likely to persist over the long term.

We propose the following planning approach based on the likelihood an event will occur to address the uncertainty associated with marsh loss due to SLR. We also suggest that the approach to communicating risk outlined by the IPCC (Mastrandrea et al. 2011), and exemplified by this case study, will help ensure consistent messaging about the probability of future outcomes when working with groups involved in conservation planning:

1. Identify areas of overlap that are predicted to be inundated in static models and unlikely or as likely as not (< 66% chance) to adapt based on dynamic models, and exclude those from initial consideration (Tables S2, S3).
2. Prioritize remaining patches to maximize representation of conservation benefits relative to costs based on current conditions (e.g., Klingbeil et al. 2018).
3. Identify areas of overlap with those predicted to: (a) remain above sea level in static models and (b) likely or very likely (> 66% chance) to adapt in dynamic models (Tables S2, S3). Prioritize the best of these sites based on the results from (2) because they have the highest probability of being valuable in both the short- and long-term. Sites in this group that are not ranked high in (2) should be evaluated to determine whether their value could be increased via management.
4. Prioritize next, based on the ranking in (2), those sites that are predicted to be inundated in static models but likely or very likely (> 66%) to adapt in dynamic models.
5. Finally, for areas identified as being as likely as not (33–66% chance) to adapt in dynamic models, prioritize based on (2), and focus work to improve predictions on those sites that are the highest priorities. The best of these sites are potentially also targets for management efforts to improve the chance of long-term persistence.

In order to predict potential declines in bird populations due to SLR, our approach relies on the assumption that populations will respond linearly to loss of habitat and does not explicitly consider differences in the quality of remaining habitat. These assumptions may overestimate the resiliency of populations to SLR by not accounting for changes in demographic rates, food availability, predation, or other factors that regulate persistence of tidal marsh bird populations. Alternatively, they may underestimate the ability of species to adapt, although there is little evidence that this will occur in any of the target species over the timeframes being discussed. While our approach may be a simplification, we expect our estimates to be conservative relative to alternatives that account for additional processes associated with the persistence of future populations undergoing habitat loss, but for which sufficient data currently are lacking. An additional complication is that fewer than 10% of saltmarsh patches shared similar predictions for the entire patch area: 328 were predicted to be either completely inundated or unlikely to respond dynamically, and 300 were predicted to remain above sea level or likely to respond dynamically (Tables A2, A3). This complication is partially due to our use of ecologically defined patches rather than uniform grid cells or hexagons, and models applied at different spatial scales may provide further insights. Ultimately, spatial considerations such as these, as well as other important considerations related to patch size, connectivity of patches, and the role of refugia, will need to be built into any prioritization of conservation actions and tailored to reflect the species and goals of conservation efforts (Warman et al. 2004).

Management and policy implementation benefits from information that is expected to be robust over time. This is problematic when future projections vary or change as a function of time, as is true in many cases where climate change will cause a progressive shift from one land cover type to another. Identifying and prioritizing areas that are both currently important, and predicted to be likely to remain stable over time regardless of future scenario or modelling approaches, are perhaps the best way to protect holdout populations (*sensu* Hannah et al. 2014). Clearly identifying sites that are have a low likelihood to support conservation goals under any circumstance may also help avoid situations where local interests might distort global priorities (Klingbeil et al. 2018). Finally, when available, folding information on the likelihood of a dynamic response to climate change into planning decisions might help distinguish sites where management has the greatest opportunity to be effective.

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Author contributions BTK, JBC, CSE, TPH, AIK, BJO, and WGS conceived the idea. MDC, CRF, EEL and WAB collected data, BTK EEL and WAB analyzed the data, BTK and CSE wrote the paper.

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Data availability Data are available in the online supplementary material and ArcGIS shapefiles for 2030 (Table S2) and 2050 (Table S3) will be available for download from Data Basin: https://databasin.org/galleries/545d42aee349487baf5fa5586d647fe5. Data for the coastal response outcomes from Lentz et al. (2015) referenced in this paper are published in the following repository: https://doi.org/10.5066/F73J3B0B.

Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

Ethical approval No live birds were used in this study.

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