



Foundations of modeling resilience of tidal saline wetlands to sea-level rise along the U.S. Pacific Coast

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Abstract

Context Tidal saline wetlands (TSWs) are highly threatened from climate-change effects of sea-level rise. Studies of TSWs along the East Coast U.S. and elsewhere suggest significant likely losses over coming decades but needed are analytic tools gauged to Pacific Coast U.S. wetlands.

Objectives We predict the impacts of sea-level rise (SLR) on the elevation capital (vertical) and migration potential (lateral) resilience of TSWs along the Pacific Coast U.S. over the period 2020 to 2150 under a 1.5-m SLR scenario, and identified TSWs at risk of most rapid loss of resilience. Here, we define vertical resilience as the amount of elevation capital and

lateral resilience as the amount of TSW displacement area relative to existing area.

Methods We used Bayesian network (BN) modeling to predict changes in resilience of TSWs as probabilities which can be useful in risk analysis and risk management. We developed the model using a database sample of 26 TSWs with 147 sediment core samples, among 16 estuary drainage areas along coastal California, Oregon, and Washington.

Results We found that all TSW sites would lose at least 50% of their elevation capital resilience by 2060 to just before 2100, and 100% by 2070 to 2130, depending on the site. Under a 1.5-m sea-level rise scenario, nearly all sites in California will lose most or all of their lateral migration resilience. Resilience losses generally accelerated over time. In the BN model, elevation capital resilience is most sensitive to elevation capital at time t , mean tide level at time t , and change in sea level from time 0 to time t .

Conclusions All TSW sites were projected with declines in resilience. Our model can further aid decision-making such as prioritizing sites for potential management adaptation strategies. We also identified variables most influencing resilience predictions and thus those potentially prioritized for monitoring or development of strategies to prevent loss regionally.

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Introduction

Tidal saline wetlands (TSWs) provide a wide array of ecological and social values for key wildlife habitats, biodiversity conservation, recreation sites, and traditional cultural uses, and provision of numerous ecosystem services including carbon sequestration, soil retention, flood and erosion control, shellfish industries, plant productivity, and more (Barbier et al. 2011; Mcleod et al. 2011; DeLaune and White 2012; Peck et al. 2020). Sea-level rise will result in the potential loss of many of these low-lying ecosystems (Kirwan and Megonigal 2013; Nevermann et al. 2023; Schibalski et al. 2022). Coastal TSWs are particularly vulnerable to impacts of climate change, particularly from sea-level rise, increases in temperature, changes in precipitation patterns, increases in storm surges, and other factors (Tebaldi et al. 2012; Grieger et al. 2020), putting marsh vegetation and associated wildlife and ecosystem services at risk (Thorne et al. 2012; Rosencranz et al. 2018). Here, based on the definition in Federal Geographic Data Committee (2013), we define TSW as an area with emergent halophytic plants which are regularly flooded and drained by the tides (also known as tidal wetland, marsh).

The degree to which TSWs are vulnerable can be anticipated by gauging their capacity to respond to sea-level rise by building elevation to maintain their position in the tidal frame or habitat displacement upslope—“upland migration” (Kirwan et al. 2016; Holmquist et al. 2021; Osland et al. 2022). Predicting such vulnerability is key to prioritizing planning and management activities for climate change adaptation and ecosystem conservation management (Berman et al. 2020; Lyons et al. 2020) in the coastal zone.

For this analysis, we differentiate between resistance and resilience (Griffiths and Philippot 2013; Holling 1973). Resistance refers to the capacity of a system to remain unchanged under a stressor. A more appropriate measure for TSWs is that of resilience, which can be defined as the capacity of a system to be changed by an exogenous stressor, such as sea-level rise, yet still provide some degree of its values and services (Ferrier et al. 2020; Marcot 2021). Hessburg et al. (2013, p.806) also defined resilience as “the inherent capacity of a landscape or ecosystem to maintain its basic structure and organization in the face of disturbances, both common and rare.”

The resilience of ecological systems is influenced by many factors including characteristics of the biotic and abiotic environment and the degree and type of stressors (Scheffer and Carpenter 2003; Donaldson et al. 2019). Measures of resilience have been used in analyses of socio-ecological systems (Allen et al. 2018), functional diversity of rangelands (Chillo et al. 2011), restoration of forest lands compromised by wildfire (Hessburg et al. 2015), and much more. Some definitions and measures of resilience include estimates of recovery times to pre-disturbance conditions (e.g., Schibalski et al. 2018). However, this component of resilience is not applicable to the impacts of TSWs to monotonic and irreversible global sea-level rise as projected by Sweet et al. (2022) to be 1.5 m under the National Oceanic and Atmospheric Administration (NOAA) report Intermediate-High emissions scenario. For the Pacific Coast of North America, relative sea-level rise projections range from less than 0.20 m to over 2.0 m by 2100, and up to 3.70 m by 2150; the magnitude is dependent on realized greenhouse gas emissions and atmospheric warming over the coming century and on specific locations along the coastline (Sweet et al. 2022). Here, we follow recommendations by Capdevila et al. (2021) to use existing theoretical frameworks to define resilience, to use common and comparable metrics to measure resilience, to denote and define pre- and post-disturbance states, and to explicate the type of disturbance and regime impacting the system.

TSW are located along low-energy coastlines and can adapt to changing water levels and reside in dynamic equilibrium with water levels. Elevation-building processes related to water level datums include below and above ground processes related to sediment and organic matter contributions (Callaway et al. 2013). The amount of elevation in which a TSW can exist above a water level datum has been called “elevation capital” (Cahoon and Guntenspergen 2010). If there is an insufficient amount of material to build elevation then submergence with accelerating sea-level rise will occur (Kirwan and Megonigal 2013) with consequent loss of elevation capital.

Previous assessments of the impact of climate change and sea-level rise on coastal wetlands (coastal marshes) in the U.S. have focused on regions of the Atlantic Coast (Titus et al. 2008; White et al. 2022) and Gulf of Mexico (Geselbracht et al. 2011; Enwright et al. 2016), including coastal Florida

Everglades (Ross et al. 2022), and on tidal marsh and tidal freshwater forested wetlands (Maegonigal et al. 2016; Stagg et al. 2016) and other coastal freshwater wetlands (Grieger et al. 2020). Thorne et al. (2018) evaluated the response to a range of sea-level rise scenarios of a selected set of 14 tidal wetlands along the U.S. Pacific Coast and reported that all high- and middle-marsh habitats would be lost, and 83% of the current tidal wetlands would become unvegetated by 2110 under a high rate of sea-level rise. This type of mechanistic modeling is constrained to tidal wetlands with available site-specific data, making it difficult to expand the analysis outside of the original data domain. Brophy and Ewald (2017) provided maps of current and future tidal wetlands in Oregon based on elevation data but did not specifically model wetland response and resilience from other dynamic factors such as sea-level rise.

Coastal wetlands can be vulnerable to sea-level rise by loss of elevation relative to a tidal datum (vertical) capital or by loss of lateral (horizontal) capital, the degrees to which are determined by sediment accretion, topography, plant communities, and human modifications or barriers in the estuary. As sea level rise occurs, the margins of a TSW can become inundated or erode leading to loss in TSW area; however, at upper elevation boundaries of the TSW, there may exist potential for the TSW to migrate inland.

In analyses of coastal estuaries in Europe and Atlantic Coast U.S., Kirwan and Temmerman (2009) concluded that, under continuous sea-level rise, modeled accretion rates lagged sea-level rise rates by about 20 years and will never reach equilibrium. Kirwan and Guntenspergen (2010) found that tidal range was an important factor contributing to resilience, concluding that coastal wetlands with high tidal ranges were more stable. Further, Kirwan et al. (2010) found that nonlinear feedbacks among site factors including inundation, plant growth, organic matter accretion, and sedimentation rate could provide for some resilience to sea-level rise; however, under projections of higher sea-level rise, coastal wetlands were predicted to be fully inundated by the end of the current century. Wetland area gains under sea-level rise have been observed in Big Bend, central west coastal Florida, if sediment and upland migration space is available (Raabe and Stumpf 2016). Enwright et al. (2016) and Osland et al. (2022) also found landward

migration opportunities for coastal wetlands in large regions of the Gulf of Mexico, especially Louisiana, presumably providing gains in area with sea-level rise. Schieder et al. (2017) suggested that the loss of wetlands due to SLR in the Chesapeake Bay of Virginia were roughly equivalent to gains from upland migration.

Field measurements using sediment cores, marker horizons, or surface elevation tables (Cahoon et al. 2002) can provide information on whether a TSW is building elevation to outpace sea-level rise (Rogers et al. 2012; Thorne et al. 2013; Webb et al. 2013; Steinmuller et al. 2020; Langston et al. 2022). This information is often published to understand vulnerability or resilience of the TSW. Most modeling of coastal wetland response to sea-level rise is mechanistic and as such requires much data, but can provide high resolution analyses, down to a few meters, as used in the models WARMER (Wetland Accretion Rate Model of Ecosystem Resilience; Swanson et al. 2014) and MEM (Marsh Equilibrium Model; Morris et al. 2012). State-transition models of sea-level rise are simpler and have been employed extensively (e.g., SLAMM, Sea Level Affecting Marshes Model; Geselbracht et al. 2011; Linhoss et al. 2013) but may be coarser, lack resolution in many areas, and do not express variation and uncertainty. Other models of marsh response to sea-level rise can be theoretical (e.g., Allen 1997, Carr et al. 2020) by which to generate hypotheses about causal relationships.

Thorne et al. (2018) conducted mechanistic modeling using the WARMER model to simulate biological and physical processes, including sea level rise, that affect marsh accretion and marsh elevation. This approach requires extensive modeling capabilities and field data. Our study illustrates a Bayesian network approach that uses a framework that is not explicitly mechanistic and does not require site specific extensive sediment and biological data, but can also provide similar outcomes for sea level rise vulnerability. This type of modeling is needed because many decision makers may not have mechanistic modeling abilities nor the resources to collect site specific biophysical data. and could use the approach outlined here to generate similar outcomes. This use of Bayesian networks is a novel approach and has not been applied to the Pacific Coast, and we believe this approach can provide lessons learned to transfer the applicability to sites without robust datasets.

For the current analysis we chose to model the influence of sea-level rise on TSW resilience with causal structures represented in a Bayesian network (BN). BNs are widely used in environmental modeling (Aguilera et al. 2011), including prediction of impacts on wetlands and coastal conditions (e.g., Sahin et al. 2019; Rachid et al. 2021). General methods of developing BN models were reviewed by Darwiche (2009), Fenton and Neil (2012), Kjaerulff and Madsen (2007), and others. BNs are structured as directed acyclic graphs (networks without feedback cycles) and they depict causal and correlational links among variables as conditional probabilities. Input variables in BNs are denoted with prior probabilities represented in Dirichlet distributions, and outcome results are calculated as posterior probabilities using Bayes' Theorem (Fenton and Neil 2012).

Two main advantages of modeling the resilience response of TSWs to sea-level rise in BNs over the use of "frequentist" multivariate statistical models are that (1) BNs explicitly denote uncertainties as probability distributions that propagate accordingly throughout the network, and (2) BNs can provide calculated results in the face of missing data where default prior distributions are used (Darwiche 2009; Aguilera et al. 2011; Marcot 2019). Further, BNs can be structured using empirical data, expert knowledge, or a combination (Marcot 2019), and as new observations are collected, parts or all of a BN model can be updated, improving the accuracy of model predictions. BNs serve well to inform vulnerability, can identify strength of evidence and areas of key uncertainties, and can provide clear expressions of knowledge and probability distributions to inform risk analyses and decision-making under uncertainty. In our current study, the Bayesian network modeling approach addressed results for 26 TSWs, whereas Thorne et al. (2018) covered 12 study sites that overlapped, which means our study expanded to 14 additional TSWs.

Gutierrez et al. (2011) developed a Bayesian network model predicting changes in shorelines and vulnerability of environments along the Atlantic Coast, U.S., and concluded that BNs are useful for depicting important factors affecting coastal changes from sea-level rise as probability predictions aiding coastal management decisions. The challenge in the current effort was that the dynamics of conditions, defining the structure of a prediction model, for wetlands

along the U.S. Eastern Seaboard are significantly different than those along the Pacific Coast, and at a scale relevant to projections of individual TSWs (Thorne et al. 2015a, b). TSWs of the Pacific Coast sit within a different biogeomorphic setting than they do along the Atlantic Coast (Osland et al. 2019). TSWs along the Pacific Coast experience mixed semi-diurnal tides (flooded with two high tides a day), tend to contain mineral-dominated soils (Callaway et al. 2012a), and contain different vegetation communities and climate zones than do wetlands on the Atlantic Coast (Janousek et al. 2019). These differences required devising a new causal framework applicable to the Pacific Coast region for informing management.

The overall objective of this effort was to devise a causal structure more specific to Pacific Coast U.S. conditions and convert it to a BN based on the current state of understanding. We compiled a database of selected TSWs by which to parameterize and calibrate the BN model; run the BN model on incremental future decadal conditions of sea-level rise and project the resilience of each selected TSW; interpret results in terms of applying the model to all Pacific Coast U.S. TSWs to aid management decision-making; and explore potential future updates and improvements to the model.

Methodology

Study areas

This project focused on TSWs along the Pacific Coast of the continental U.S., namely coastal California, Oregon, and Washington. The topography, hydrogeomorphology, and patterns of human development and occupation of TSW conditions in this region vary significantly among estuaries (Fig. 1). Some of the coastline contains densely-populated urban centers (e.g., Los Angeles, California) or more rural estuaries that are dominated by agriculture and logging (e.g., Willapa Bay, Washington). Some TSWs are development-bounded such as Newport Bay in urban southern California, and others are seasonally blocked from direct ocean influence by sand bars such as Big Lagoon in Northern California. Central San Francisco-San Pablo-Suisun Bays EDA, California (37,438 ha), and Puget Sound EDA, Washington (2914 ha), are two of some of the largest estuaries



Fig. 1 Examples of tidal saline wetlands along the Pacific Coast U.S. illustrating the diversity of topographic and development settings. **a** Golita Slough, Golita Slough Ecological Reserve, California, with a variety of estuarine, riverine, and other environments amidst a history of diking and channelization (photo: K. Backe, USGS); **b** Brian Booth—Beaver

Creek State Park, Oregon, connected to but constrained by old-growth conifer forest bluffs (photo: B. Marcot, USFS); **c** Tijuana Slough, Tijuana Estuary, California, constrained by developments (photo: K. Thorne, USGS); **d** Skokomish, Puget Sound, Washington, restored from channelized agricultural lands (photo: K. Thorne, USGS)

in the U.S. with a mosaic of urban development and agriculture. In this analysis, we calculated resilience by estuarine drainage area (EDA; Frazier et al. 2013). An EDA consists of the terrestrial and water components of a watershed that directly drains into an estuary and that contains a TSW.

Data collection

Here, we define vertical resilience as the amount of elevation capital and lateral resilience as the amount of TSW replacement area relative to existing area.

Geomorphic setting

Elevation, Mean High Water (MHW) and Mean Tide Line (MTL) were determined for each core location using VDatum (<https://vdatum.noaa.gov/>), with the range of maximum cumulative uncertainty for this region being noted as 6.5–8 cm. Elevation [m, North American Vertical Datum of 1988 (NAVD88)] for each core location is denoted by z and was obtained from the Coastal Carbon Atlas database (<https://ccrcn.shinyapps.io/CoastalCarbonAtlas/>), Thorne et al. 2015a, b), (2016). Here, elevation capital, Z^* , is a dimensionless ratio of the elevation

relative to MTL (Swanson et al. 2014), calculated as $Z^* = (z - MTL)/(MHW - MTL)$.

Accretion rates

In our database, individual cases pertain to sediment core sample locations within TSW sites. We used results of sediment core analyses based on isotopes of cesium (Cs237; $n=64$ core samples) and lead (Pb210; $n=87$ core samples) as date-markers. Core samples are denoted with corresponding latitude and longitude locations, and the core data were acquired from a variety of literature sources (Callaway et al. 2012b; Peck et al. 2020; Thorne et al. 2015a, b, 2016). The resulting sample of 147 cores derives from 26 TSW and 16 EDA ranging latitudinally from northern Washington to southern California (Supplementary Information Fig. A).

Elevation capital

Elevation capital is the material accumulated during tidal wetland development that establishes the height of a wetland within the tidal frame (i.e., conversion from subtidal open water to intertidal mudflat to emergent marsh) (Cahoon and Guntenspergen 2010; Cahoon et al. 2018) and vertical resilience is the

maintenance of elevation capital determined by rates of marsh surface elevation change relative to the sea-level rise for the same time interval.

Current tidal saline wetland extent

Current TSW extent in hectares for each EDA was determined using the Coastal Change Analysis Program (C-CAP) Regional Land Cover and Change (National Oceanic and Atmospheric Administration)¹. Estuarine Emergent Wetland category was used to calculate area by EDA.

Migration capacity

TSW migration capacity was determined using the methodology presented in Osland et al. (2022) and was acquired from Chivoiu et al. (2022). We examined the migration potential for a 1.5 m global mean sea level rise scenario, which corresponds to the 2100 Intermediate-High emission scenario and the 2150 Intermediate-Low and Intermediate emission scenarios (Sweet et al. 2022).

Database of tidal saline wetlands

Our case file database is organized hierarchically by EDA name, TSW name, and site locations of sediment core samples (available at <https://doi.org/10.59381/efgk0939>). The database consists of 16 EDAs, 26 TSWs, and 147 core sample locations, with 1 to 7 TSWs per EDA, and 1 to 17 cores per TSW, distributed over selected sites in coastal California, Oregon, and Washington (Table 1).

Development of the Bayesian network model

We began an iterative process of developing our BN model in a graphical software application (Netica©; Norsys, Inc.). We first reviewed the available literature on the hydrodynamics of coastal wetlands and the influence of sea-level rise, which focused on coastal regions elsewhere or only on specific locations along the U.S. Pacific Coast. We built a succession of BN model structures as causal networks denoting TSW

dynamics using this prior information and from our collective empirical experience. We also explored statistical relationships among variables in the data that we initially compiled from selected sites on the Pacific Coast, for example accretion rate as a function of wetland elevation, as derived from the 147 sediment core samples (Fig. 2). Our causal network evolved as a series of concept maps exploring hypothesized and expected relationships among variables, and our data analyses led variously to discovery of poor correlations, non-significant and potentially spurious correlations, and of unexpected but salient correlations among variables, all of which led to incrementally amending and improving the network. We have traced these steps in model development in the spirit of full disclosure and documentation (Supplementary Information TSW Model Development Phases).

One of the main drivers in the model is, naturally, change in sea level over time. For this metric, we used the findings from the NOAA report (Sweet et al. 2022) which are based on future increase in mean sea level relative to current sea level at time 0 (2020), gauged to a projection of an ultimate 1.5-m sea-level rise. Values for change in sea level varied spatially, which we read from Sweet et al.'s 1-degree grids for each of the TSW locations in our case file database and represent the medium 1.5 m scenarios. We also assumed that, at time 0, mean sea level is identical to mean tide level (MTL), as evidenced by Woodworth (2017) and that tidal datums relative to MTL remained constant with SLR. We additionally compiled values on many more variables in the database than we ultimately used explicitly in the final BN model, but were useful during the model evolution phases to explore correlations and degrees of predictability among variables (Supplementary Information TSW Model Development Phases).

During our explorations of alternative causal network structures and data relationships, we produced a series of functioning predictive BN models. The final model structure was developed by a combination of our statistical explorations of data relationships and our experience and expert knowledge on the hydrodynamics of TSWs. The BN model uses continuous-value variables that are discretized into states with exclusive value ranges based on the known values in our compiled TSW case file database. We experimented with varying the number of discretized

¹ <https://coast.noaa.gov/digitalcoast/data/ccapregional.html>, 2016.

Table 1 Locations by U.S. state and names of 16 estuary drainage areas (EDAs) and their 26 tidal saline wetlands (TSWs), and number of sediment cores, used in the case file database to parameterize the Bayesian network model predicting TSW resilience to sea-level rise

EDA-estuary drainage area	TSW-tidal saline wetland	No. sediment cores per TSW
CALIFORNIA (n = 5 EDAs, 11 TSWs, 74 cores)		
Central San Francisco-San Pablo-Suisun Bays	Bolinas Lagoon	1
Central San Francisco-San Pablo-Suisun Bays	Browns Island	11
Central San Francisco-San Pablo-Suisun Bays	China Camp	12
Central San Francisco-San Pablo-Suisun Bays	Coon Island	17
Central San Francisco-San Pablo-Suisun Bays	Petaluma River	5
Central San Francisco-San Pablo-Suisun Bays	Rush Ranch	12
Central San Francisco-San Pablo-Suisun Bays	Whales Tail	6
Newport Bay	Newport Marsh	1
San Diego Bay	Sweetwater Marsh	2
Santa Barbara Channel	Carpinteria Marsh	1
Tijuana Estuary	Tijuana Slough	6
OREGON (n = 8 EDAs, 10 TSWs, 62 cores)		
Alsea River	Alsea	10
Columbia River	Youngs	5
Coos Bay-Tenmile	Coos Bay	2
Coquille River	Bandon	2
Coquille River	Coquille	6
Nehalem River	Nehalem	6
Salmon River	Salmon River	10
Siletz Bay	Siletz	2
Wilson-Trusk-Nestuccu-Netarts Bay	Netarts	15
Wilson-Trusk-Nestuccu-Netarts Bay	Tillamook	4
Washington (n = 3 EDAs, 5 TSWs, 11 cores)		
Dungeness-Elwha	Washington Harbor	1
Grays Harbor-Willapa Bay	Grays Harbor	2
Puget sound	Nisqually River Delta	5
Puget sound	Padilla Bay	1
Puget sound	Skokomish	2

states to best balance model precision and accuracy because, in BN modeling, more states provide greater precision but with a potential tradeoff of accuracy. Given the sample size of cases in the database, and the model structure (numbers of parent nodes), we decided on using no more than 5 states per node for each continuous-value variable.

We used the empirical data from our TSWs case file to parameterize the prior (unconditional) probabilities and the conditional probability tables, by employing the widely-used machine-learning expectation maximization (EM) algorithm (in Netica). EM is a convergent log-likelihood function that iteratively adjusts probability values in the model so as to best fit to the case file data (Do and Batzoglou 2008), and its

advantage is to efficiently and effectively parameterize models for optimal parameter output to best fit to a known set of case examples (Zhou et al. 2010). Use of the empirical data set for informing values of probability distributions is an important step in ecological Bayesian modeling (Wesner and Pomeranz 2021), and essentially serves to calibrate the model to the overall conditions of all cases in the database.

We expressed TSW resilience to sea-level rise in the model along two axes *elevation capital (vertical) resilience* and *migration capacity (lateral) resilience*. We further explored alternative means of combining elevation capital and lateral migration into one overall resilience outcome variable, such as by a simple sum of their Weber fraction values, but we ultimately

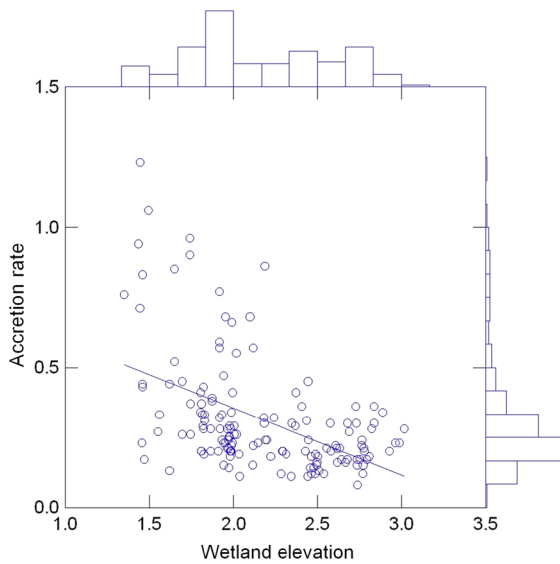


Fig. 2 Correlation of core sample sediment accretion rate (m/yr; n = 147 core samples) by current wetland elevation (m) for 26 tidal saline wetlands along the U.S. Pacific Coast, with best-fit linear regression and histograms of data frequencies on each axis (Pearson $r = -0.485$, $p < 0.001$)

omitted that outcome node from the model as it proved unnecessarily redundant to, and less informative than, the individual elevation and lateral migration resilience outcomes.

Projections of elevation capital resilience were time-specific because the model calculated mean tide level and TSW elevation for each time period, in part as a function of year, spanning 2020 to 2150 by decade. In contrast, calculations of TSW lateral migration resilience were invariant to time, as they were based on comparing current TSW extent with TSW upslope migration capacity at the full 1.5-m sea-level rise projection. This approach was chosen given the overall lack of understanding on TSW migration processes and rates to parameterize a temporal model approach. Therefore, we focused on the total area possible for upland migration.

The BN model calculates resilience outcomes displayed as probability distributions among the 5 discretized states in each of the output nodes (Fig. 3). These probability distributions represent the propagation of uncertainties and distributions of values in other variables in the model as known from the case

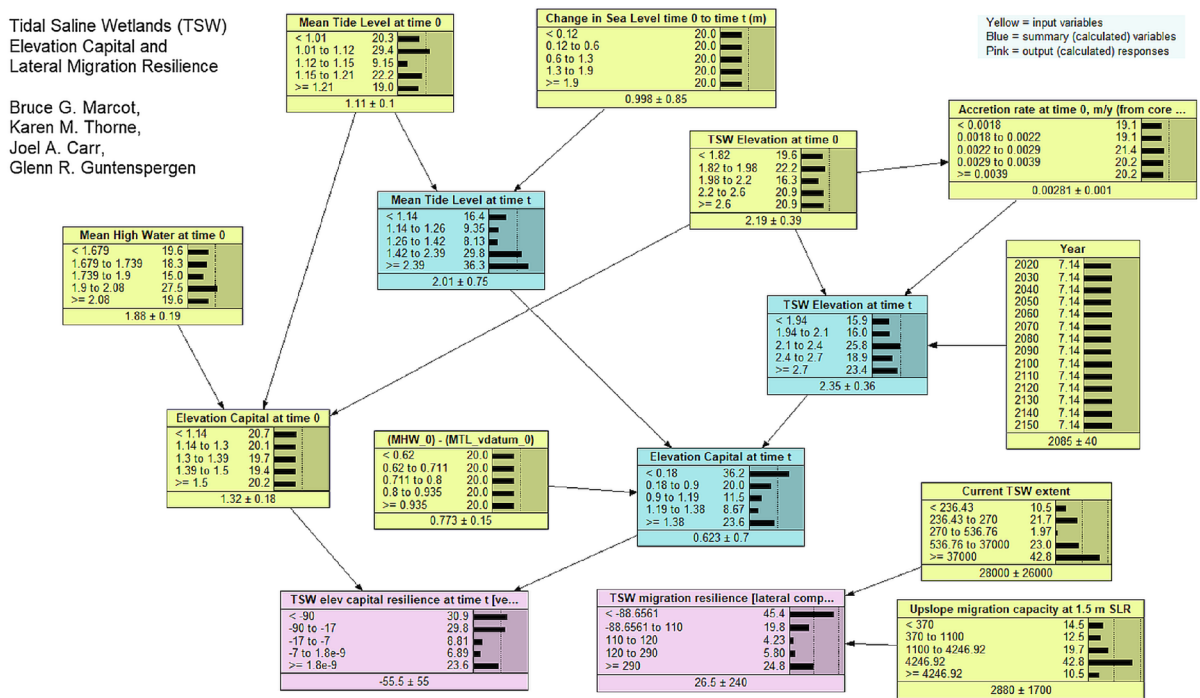


Fig. 3 Bayesian network model analyzing time-specific elevation capital resilience and migration resilience of tidal saline wetlands (TSW) along the Pacific Coast U.S. Note that the val-

ues represented in the bottom of each node in the model ($x \pm y$) are the expected value ± 1 standard deviation (assuming Gaussian distributions)

Table 2 Equations used in 5 nodes of the Bayesian network model predicting tidal saline wetland (TSW) resilience to sea-level rise along the Pacific Coast, U.S.

Model variable	Equation number	Equation ^a
Mean tide level at time t	1	$MTL_vdatum_t = MTL_vdatum_0 + RSL_t$
TSW elevation at time t	2	$TSWElev_t = (TSWElev_0) + (AccRate_0 * (t-2020))$
Elevation capital at time t	3	$ElevCap_t = (TSWElev_t - MTL_vdatum_t) / Denom$
TSW elevation capital resilience at time t	4	$TSWEleRes_t = ((ElevCap_t - ElevCap_0) / ElevCap_0) * 100$
TSW migration resilience	5	$TSWMigRes_t = ((UpMigCap_t - CurrWetExt) / CurrWetExt) * 100$

^aVariables and abbreviations used and units of measure

AccRate_0 Accretion rate at time 0 (m/yr); *CurrWetExt* Current wetland (TSW) extent (ha); *Denom* (MHW_0)-(MTL_vdatum_0) (m); *ElevCap_0* Elevation capital at time 0 (dimensionless unit; Swanson et al. 2014); *ElevCap_t* Elevation capital at time t (dimensionless unit; Swanson et al. 2014); *TSWMigRes_t* TSW migration resilience (dimensionless unit; Weber fraction); *TSWElev_0* TSW elevation at time 0 (m); *TSWElev_t* TSW elevation at time t (m); *TSWEleRes_t* TSW elevation capital resilience at time t (dimensionless unit; Weber fraction); *MHW_0* Mean high water at time 0 (m); *MTL_vdatum_0* Mean tide level at time 0 (m). *MTL_vdatum_t* Mean tide level at time t (m); *RSL_t* Change in sea level time 0 to time t (m); *t* Year; 10-year increments from 2020 to 2150; 0 in variable names denotes year 2020; *TSW* Tidal saline wetland. *UpMigCap_t* Upslope migration capacity at time t (ha)

file database of TSWs. On a site-by-site basis, the probability distributions in the resilience outcome nodes can be used to denote the degree of uncertainty of resilience effects, although projection calculations always led to a strongly dominant probability outcome for a single state. However, for greater simplicity, to compare resilience effects among sites and time periods, we used the expected value from each calculation (Fig. 3) which is the sum of the midpoint of each state’s range of values weighted by the calculated probability of that state.

Our final selection of 15 model variables (listed in footnote in Table 2) constituted the building blocks for the causal network. We parameterized five summary variables (nodes) in the final BN model with equations either derived from the literature, or, for representing elevation capital and lateral migration resilience, by using Weber fractions comparing starting (2020) conditions to those in future time periods (Table 2). All elevation values in the Table 2 equations are in meters. Equation 1 computes the mean tide level at specified time period t (taken from the VDatum source cited further above), as the sum of the mean tide level at time 0 (present) and the relative sea level at time t. Equation 2 computes the elevation of the TSW at time t as the sum of the TSW’s elevation at time 0, and the product of the per-annum accretion rate and the number of years from time 0 to time t. Equation 3 computes the elevation capital of the TSW as the difference between the TSW elevation at time t and the mean tide level of the TSW at time t (from

VDatum), normalized by the difference between the mean high water level at time 0 and the mean tide level at time 0 (from VDatum). Equation 4 calculates the TSW elevation capital resilience at time t as a Weber fraction by comparing the change in elevation capital from time 0 to time t, per elevation capital at time 0, and converting this fraction to a [0,100] percentage scale. Equation 5 calculates the TSW migration resilience independent of the elevation capital resilience, also as a Weber fraction by comparing the upslope migration capacity at time t to that at time 0, per upslope migration capacity at time 0, and converting the fraction to a [0,100] percentage scale. In compiling the parameterized model, for model nodes containing equations we used Netica’s equation-to-table function that discretizes each node’s equation to create a discrete conditional probability table (Supplementary Information Model Probabilities).

Because the model was structured in part with our equations calculating specific outcomes, there was no other database by which we could conduct independent model validation testing, and our case file database was too small to employ cross-validation methods (Marcot and Hanea 2021). To this end, we ensured that the model at least adhered to *computational reproducibility*, which is defined as obtaining consistent results using the same input data, computational steps, methods, code, and conditions of analysis (NASSEM 2019, p. 46), by providing access to the final model, all of its values and components, and the case file database. However, lacking an independent

database by which to strictly test model validation, we did strive to test *model replicability*, which is defined as obtaining consistent results across studies of the same issue (NASEM 2019, p. 46), by comparing our results to the projections of TSW resilience from other studies. Model replicability may be an important indicator of the utility and reliability of our final predictive model for its intended application to other coastal TSWs along the U.S. Pacific Coast.

We then conducted model sensitivity analysis to determine the degree to which the TSW elevation capital resilience node is sensitive to the other nodes in the model used in its calculation. Sensitivity of continuous-value nodes is best expressed by calculations of variance reduction (and normalized as percent variance reduction), which is the expected reduction in variance of an outcome node due to the incremental influence of an input node (Pearl 1988; see Marcot 2012 for equation used). Greater values of variance reduction denote greater sensitivity of the outcome node to a given input node. Variables (nodes) with high sensitivity, most affecting outcome predictions of TSW resilience, and that are also poorly quantified or studied, may helpfully suggest priorities for future inventory, monitoring, or research.

Projecting elevation and migration resilience to sea-level rise

Each of the 147 cases in the database pertains to a unique sediment core sample. Although the final BN model excluded explicit use of sediment core data, those data were instrumental in the included variable of accretion rate as derived from the sediment core values. Further, other input variables in the model were specified for each sediment core location, so we used the model to calculate TSW resilience for each sediment core site individually.

We used our model to project the degree of elevation capital and lateral migration resilience for each sediment core sample location in each TSW and EDA in our database, for each decadal period from 2020 to 2150. We present results of elevation capital resilience by individual sediment core sample in each TSW and for each TSW averaging results among the core samples, and also, as comparison, by EDA. Given that core samples were not evenly distributed by TSW or elevation we decided an average accretion rate for each TSW was the most suitable option. The

plotted depictions can provide a site manager with information on how quickly a given TSW and specific sediment core location might lose specific percentages of its resilience, and to potentially help prioritize wetlands for management actions based on those losing their resilience the quickest.

Results

Here we present results of our case file database of TSWs, structure of the BN model, model sensitivity analysis, and projections of TSW elevation capital resilience and lateral migration resilience.

Bayesian network model

Our final BN model (Fig. 3) consisted of 15 nodes, 16 links, 8 unconditional prior probability tables, 7 conditional probability tables, and 3449 unconditional or conditional probability values (Supplementary Information Model Probabilities). We parameterized the model with the case file database of the 147 sediment core samples (Supplementary Information Tidal Saline Wetland Case File Database). In this way, the prior probability distributions of the input variables (Fig. 3) represent the frequency distributions of values from the case file database.

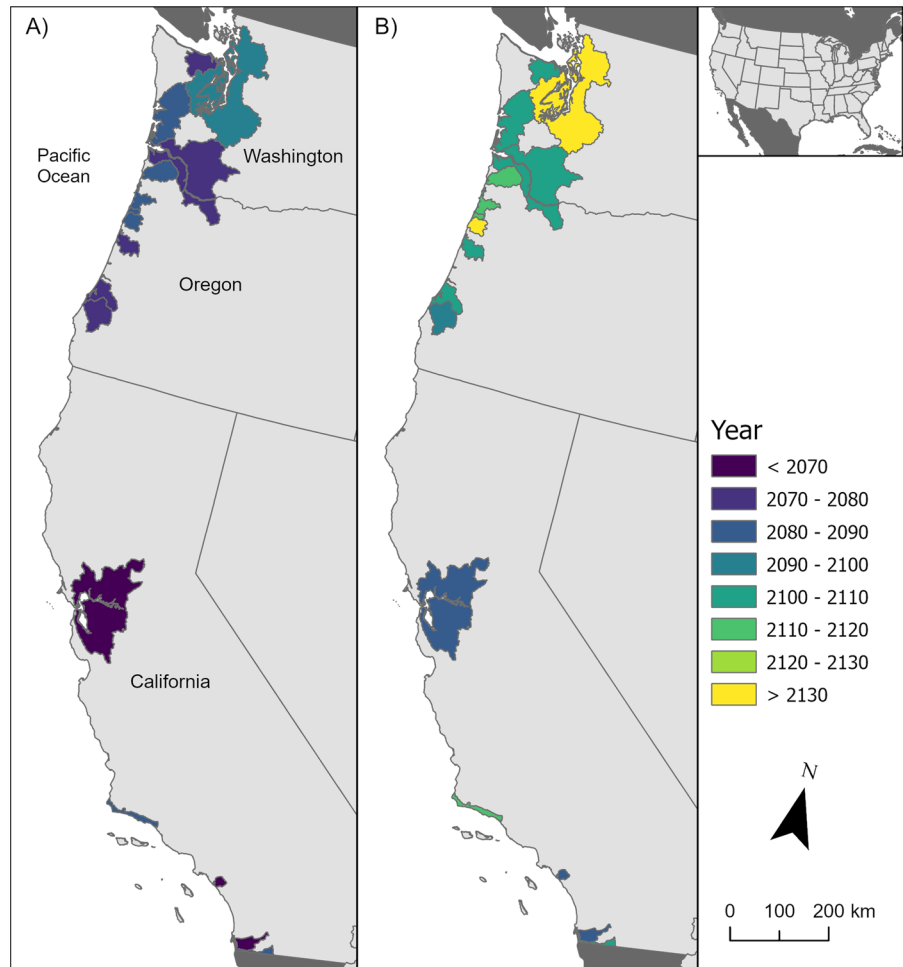
The BN model projects the degree of TSW elevation capital resilience as the percent change of elevation capital of a TSW from current to each future decade of 2020 to 2150, where values >0 mark increases in resilience (rarely occurring, and only temporarily) and <0 mark decreases, with values of -100% denoting complete loss of current elevation capital resilience (Table 2). TSW lateral migration resilience is calculated similarly but only for the ultimate effects of a projected 1.5-m sea level rise, so is presented as time-invariant.

Projections of elevation capital resilience of tidal saline wetlands

Trends by tidal saline wetland

The TSWs vary in their predicted degree of loss of resilience over time. Projections of elevation capital resilience of the 26 TSWs along Pacific Coast, U.S. (Fig. 4), as analyzed in this study, suggest marked,

Fig. 4 Projections of the average decade in which **A** 50%, and **B** 100% loss of elevation capital resilience occurs within each estuarine drainage area based on 26 tidal saline wetlands (TSW) along the Pacific Coast U.S., 2020 to 2150, and averages among sediment core samples in each TSW. See Table 1 for U.S. state locations and estuary drainage areas of each wetland



mostly monotonic, and accelerating declines over time (Fig. 5). Our projections suggest that the 26 TSWs will lose half of their elevation capital resilience by between 2060 to just before 2100, and all of their resilience by 2070 to 2130, depending on the site.

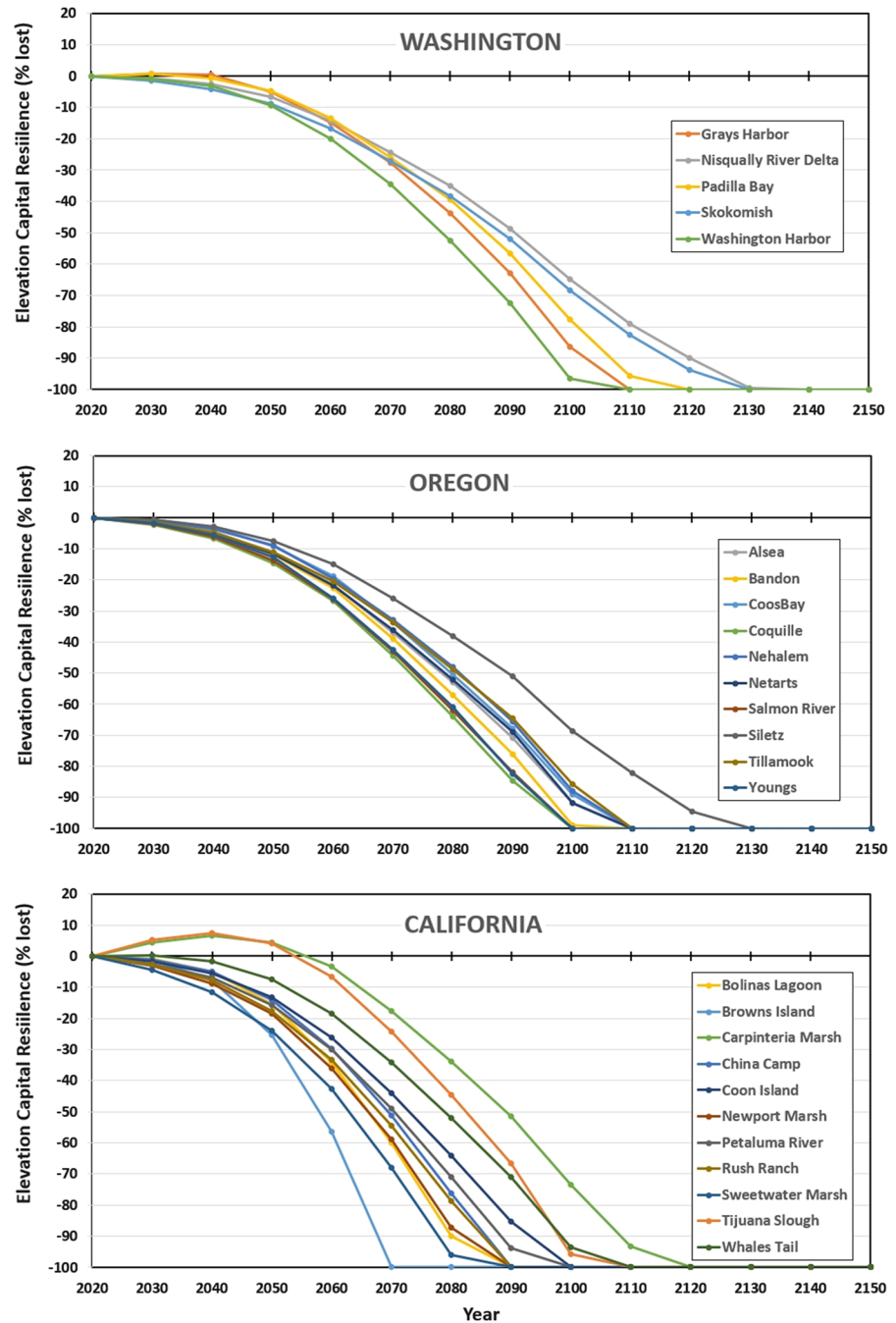
We rank-ordered the TSWs by how dire their loss of elevation capital resilience at years 2020, 2050, and 2100 will be (Table 3). Notable is that most of the sites with the highest loss of elevation capital resilience are in California (3 of the top 5 rankings in 2020, all 5 in 2050, and 4 of 5 in 2100), among 9 TSWs in that state (Bollinas Lagoon, Browns Island, Carpinteria Marsh, China Camp, Coon Islands, Newport Marsh, Petaluma River, Rush Ranch, and Sweetwater Marsh) given changes in rank-orderings of sites across time. In comparison, Oregon has only 3 sites (Bandon, Coquille, and Nehalem) ranked this way in

the top 5. Washington has none so-ranked, with our TSW sites being less immediately vulnerable than those in the other states, although all TSWs in Washington also are projected to eventually lose all of their elevation capital resilience, given time. In particular, in California, the San Francisco Bay and delta system, comprising the Central San Francisco—San Pablo—Suisun Bay Estuary Drainage Area in our database, with its seven named TSWs (Table 1), has been heavily altered since the middle 19th century with continued threats to its ecosystem functions, resilience, and possible restoration (Takekawa et al. 2006).

Trends by sediment core location

We also traced the decline in marsh elevation capital resilience at each sediment core sample location in each TSW, in part to depict the potential expected

Fig. 5 Projections of loss of elevation capital resilience of 26 tidal saline wetlands (TSW) along the Pacific Coast U.S., 2020 to 2150, based on averages among sediment core samples in each TSW. See Table 1 for U.S. state locations and estuary drainage areas of each wetland. Values of -100% denote loss of all elevation capital resilience capacity. Resilience values are based on the expected values in the resilience outcome nodes in the model (Fig. 2)



within-watershed variation of resilience (see Supplementary Information Figures B1–B22). An example is Browns Island, located in California, which, averaging across all 11 sediment core samples (Table 1), ranked in the top 5 TSW sites with the lowest elevation capital resilience in 2020, 2050, and 2100 (Table 3). It appears as the steepest curve among all

TSWs, losing 100% of its resilience the soonest, by 2070 (Fig. 5). Breaking down elevation capital resilience for each of the 11 sediment core sample locations, however, shows some variation with one sample location initially increasing in resilience over the first two decades but then quickly declining thereafter (Supplementary Information Fig. B3). A few other

Table 3 Rank orders of 26 tidal saline wetlands (TSWs) along the U.S. Pacific Coast by their elevation capital resilience for years 2020, 2050, and 2100, ranked in increase order of least to most resilient

TSW	State	2020	2050	2100
Alsea	OR	14	14	16
Bandon	OR	2	12	12
Bolinas Lagoon	CA	1	6	1
Browns Island	CA	4	1	2
Carpinteria Marsh	CA	3	26	23
China Camp	CA	18	8	3
Coon Island	CA	23	10	4
Coos Bay	OR	25	17	18
Coquille	OR	16	7	5
Grays Harbor	WA	26	23	20
Nehalem	OR	5	18	19
Netarts	OR	15	13	17
Newport Marsh	CA	22	3	6
Nisqually River Delta	WA	7	22	26
Padilla Bay	WA	12	24	22
Petaluma River	CA	20	5	7
Rush Ranch	CA	6	4	8
Salmon River	OR	9	9	9
Siletz	OR	21	20	24
Skokomish	WA	11	19	25
Sweetwater Marsh	CA	17	2	10
Tijuana Slough	CA	8	25	14
Tillamook	OR	13	15	21
Washington Harbor	WA	10	16	13
Whales Tail	CA	19	21	15
Youngs	OR	24	11	11

Highlighted in each year are the five TSWs with the lowest elevation capital resilience. See Table 1 for state locations, and Fig. 4 for mapped locations, of the TSWs

States include CA California, OR Oregon, WA Washington

TSWs showed outliers of single sediment core sample locations with somewhat greater resilience (e.g., China Camp, Supplementary Information Fig. B4) or lesser resilience (e.g., Netarts Bay, Supplementary Information Fig. B10) than the average across all other core samples for those TSWs. It is noted that the core data leveraged was repurposed from other studies whose goals and choice of core location and sampling may not directly align with the specific objective of this study and as such outlier differences may be due to such discrepancy.

Trends by elevation capital resilience exceedance probabilities

Next, a different way to depict change, particularly loss, of elevation capital resilience, is with exceedance probability curves (Fig. 6). These curves depict the percent of all TSW and sediment core sample locations that will have specified levels of remaining elevation capital resilience, for each decadal time period 2020–2150. For example, in 2050, 70% of all sites will have $\leq 90\%$ of their elevation capital resilience remaining and, of these, only 10% of all sites will have $\leq 80\%$ remaining, but by 2100, 70% of all sites will have only $\leq 20\%$ of their elevation capital resilience remaining and, of these, half of all sites will have lost all of their remaining resilience. Overall, rates of decline in elevation capital resilience increase over time.

Projections of lateral migration resilience of tidal saline wetlands

As with the projections of elevation capital resilience, TSW sites and EDAs with the lowest lateral migration resilience were also found in California, with those having the highest resilience in Oregon and Washington (Fig. 7, Supplementary Information Fig. C). Much of the difference is because California sites are already laterally constrained by human development and steep topography, impeding any upland migration of TSWs under sea-level rise. For example, southern California and San Francisco Bay estuaries have extensive developed areas or steep coastlines which accounts for a latitudinal gradient of lateral migration capital resilience (Supplementary Information Fig. D), with greater resilience being found in EDAs further north. All sites, except Sweetwater Marsh (San Diego Bay), that had a positive lateral TSW migration resilience, occur in Washington and Oregon. The largest sites are in Oregon and include Bandon TSW in Coquille EDA, and Youngs TSW in the Columbia River EDA associated with the Columbia River Basin. Much of the lateral migration space in the Pacific Northwest, apart from Puget Sound, occurs up narrow riverine valleys.

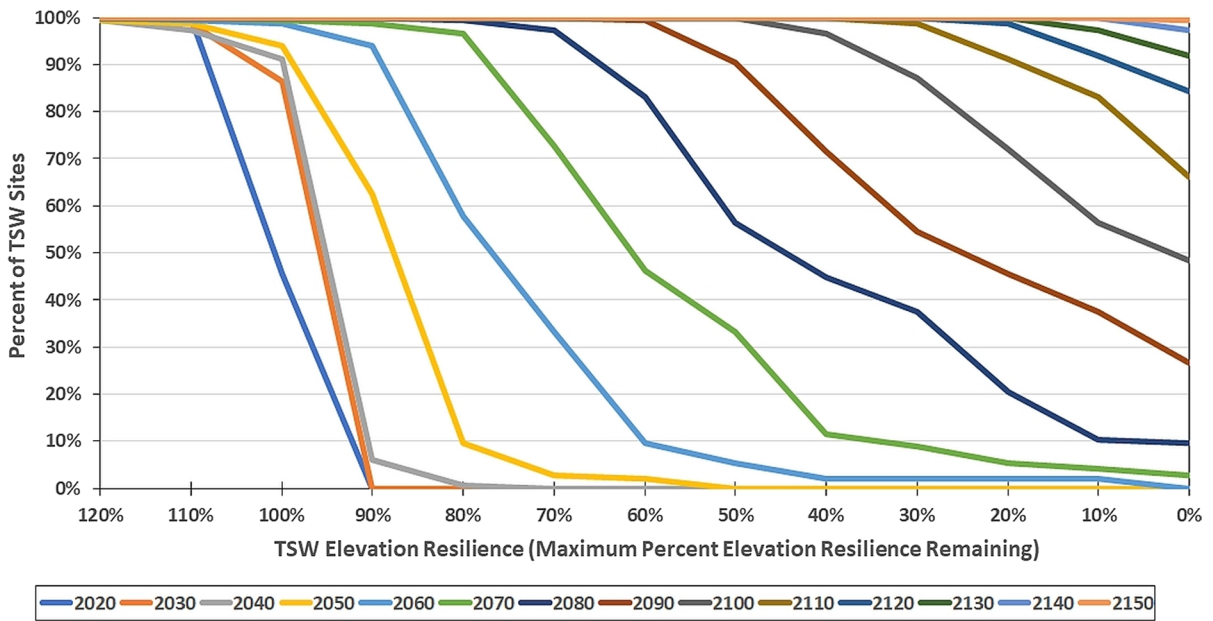


Fig. 6 Exceedance probabilities of tidal saline wetland (TSW) elevation resilience remaining, by time period (2020–2150), across all 26 sample wetlands and 147 sediment core locations along the U.S. Pacific Coast

Fig. 7 Values of lateral migration resilience of tidal saline wetlands along the U.S. Pacific Coast, where upland migration potential can occur. Values are dimensionless Weber fractions denoting percentage of upslope migration capacity of each wetland at 1.5-m sea-level rise as compared to current wetland extent (see Table 2 for equation), with higher value denoting greater migration capacity resilience (– 100 denoting loss of all resilience). See Table 1 for state locations, and Fig. 4 for mapped locations, of the TSWs

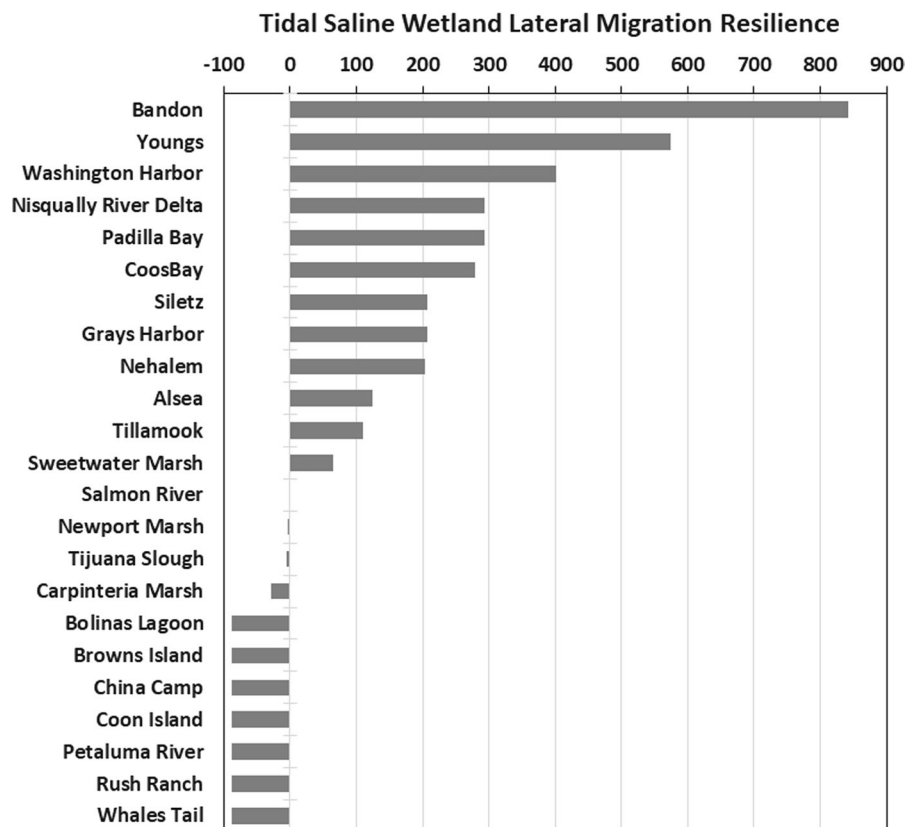


Table 4 Sensitivity analysis of tidal saline wetland (TSW) elevation capital resilience and lateral migration resilience (along the U.S. Pacific Coast) to their covariates in the Bayesian network model (see Fig. 2)

Variable	Variance reduction	Percent variance reduction
Sensitivity of elevation capital resilience		
Elevation capital at time t	2815.00	51.900
Mean tide level at time t	1224.00	22.500
Change in sea level from time 0 to time t	662.50	12.200
TSW elevation at time t	201.90	3.720
TSW elevation at time 0	96.30	1.770
Mean tide level at time 0	16.31	0.301
Elevation capital at time 0	14.88	0.274
Mean high water at time 0 minus mean tide level at time 0	11.66	0.215
Year	9.51	0.175
Accretion rate t time 0	5.71	0.105
Mean high water at time 0	0.04	0.001
Sensitivity of lateral migration resilience		
Current TSW extent	47590.00	46.600
Upslope migration capacity at 1.5-m sea-level rise	6718.00	6.580

Bayesian network model sensitivity analysis

Elevation capital resilience is most sensitive in the BN model to elevation capital at time t, mean tide level at time t, and change in sea level from time 0 to time t (each with > 10% variance reduction sensitivity). Other covariates also had sensitivity effects on resilience but with lesser influence (Table 4). Lateral migration resilience is highly sensitive to current TSW extent and to a lesser degree to upslope migration capacity at 1.5-m sea-level rise (Table 4); these sensitivity results are largely dictated by the Weber fraction equation that relates the difference in the values of these two covariates to that of current TSW extent (Table 2).

Discussion and conclusions

The process of decision-making regarding appropriate and best management of TSW is difficult especially considering the uncertainty related to the details of climate change and projected rates of sea-level rise. Climate change adaptation decision-making may be challenged by the need to choose which actions should be undertaken at what time, especially if site-specific data are uncertain or lacking. Prioritization across regional scales may be needed

to appropriately allocate resources for climate-adaptation management. There is an increasing need for tools to predict the effects of ongoing and impending impacts of sea-level rise on coastal ecosystems, particularly as extreme weather events increase in frequency and intensity, affecting coastal conditions as well as limiting inland capacities of the land base to absorb increased surface runoff (e.g., effects of vegetation denudation from catastrophic wildfires) (Sisco et al. 2017; Grace 2023; Perks et al. 2023). The model we present here accounts for some of the main hydrologic dynamics affecting resilience of TSW along the Pacific Coast, U.S., and is intended to serve as an initial advisory tool for management decisions. It can also be a platform for further consideration of other stressor events affecting TSWs. Predicting and maintaining resilience of TSWs as well could help conserve their suite of ecosystem services.

In the spirit of evaluating model replicability as discussed in methods, results presented in this paper align well with the WARMER modeling results in Thorne et al. 2018. Thorne et al. (2018) used a mechanistic modeling approach to address vertical resilience and a topography GIS spatial exercise to determine horizontal migration potential. There were 12 TSW in common analyzed by Thorne et al. (2018) and with our analysis, and both approaches found similar conclusions that elevation capital (vertical

resilience) will decrease over time with sea-level rise. This included high vertical resilience for Grays Harbor, WA (highest by 2100) using the Bayesian approach which was similar to Thorne et al. (2018). The lowest vertical resilience was at Bolinas Lagoon, CA by 2100, also similar to published results (Thorne et al. 2018). Also, Buffington et al. (2021) modeled two sites (Browns Island and Petaluma River) in San Francisco Bay-Delta that overlapped with our analysis, and we found that our results were similar to theirs for both sites, projecting the loss of elevation capital before 2100 (Fig. 5). However, Buffington et al. (2021) did not address lateral resilience explicitly.

Testing and improving the model presented here can benefit from monitoring sites and conducting research on key variables and their relationships, particularly those most uncertain but that have greater sensitivity influence on resiliency predictions, such as those affecting and affected by sediment accretion rate. In addition are the very likely effects on TSW resilience from unknown and unstudied latent variables, and from impacts of infrequent but intense events such as storm surge events (Tebaldi et al. 2012; Neumann et al. 2015; Caffrey et al. 2018). As well, there may be threshold effects or “tipping points” of sea-level rise beyond which TSW resilience may be unrecoverable (Wagener 2020). Our model, however, does not currently denote such potential abrupt changes in our predictions of TSW resilience (Fig. 4) but could be modified to include them as more information becomes available.

Our model is based on the fullest set of site data available at the time of the analysis, constituting 147 sediment core samples among 26 TSWs within 16 estuary drainage areas. Although this data set represents the results of major field sampling efforts, it is likely too sparse to use for a reliable cross-validation analysis of the BN model, given the variability among the sample values. This is a common limitation of landscape-level analyses. We recommend expanding the data set, as feasible, to include additional TSWs of diverse conditions, focusing, in part, on sites that may be experiencing greater short-term loss of resilience based on their geographic setting as discussed further above. The new data then can be integrated into the BN model to incrementally test, and then update, the model probability parameters. Further, segments of the BN model could be separately evaluated for

validity, such as estimates of future mean tide level, TSW elevation, and accretion rates.

Using our predictions of TSW resilience to sea-level rise carries the caution to land managers that various additional stressor factors as noted above are not explicitly part of our BN model. However, we do suggest that our model structure is novel and our results could be useful for initially considering prioritizing sites for management decisions, for several reasons. First, the BN model explicitly shows how missing or incomplete information can propagate through the network as uncertainty, which can be useful for risk analysis and risk management decision-making. Second, the model provides information on the rate and the degree to which different TSWs, or core sample location sites within, may lose their resilience to sea-level rise (examples given above), and thus to help prioritize sites for management consideration. Third, the model can help suggest priorities for future inventory, monitoring, and research on parameters that are most uncertain and that can most affect resilience outcomes.

Our data set on TSWs included specific values of each input variable in the BN model (the yellow nodes in Fig. 3), so the posterior probability calculations are deterministic measures of TSW resilience (Fig. 5). However, the BN model can also provide measures of uncertainty in several ways. If any of the input data values are missing or uncertain, then the model can still be run by using the default prior probability distribution of that variable, as calculated from the set of TSW cases where those values are known, or by individually specifying a particular distribution of values for that TSW. Also, we ran the model for each core sample individually in each TSW (Supplementary Information Figs. B1–B22), so the spread of those results on elevation resilience can be viewed as measures of variation or uncertainty for each TSW.

Our projections to future decades assume that physiographic and management conditions at each TSW are unchanged over time. Clearly, specific management actions could be considered (e.g., Zhao et al. 2016), especially for sites losing resilience the soonest, that may serve to slow or stabilize resilience loss. Examples may include management intended to curtail loss of TSW elevation capital resilience, such as by addition of sediment or vegetation and nutrients to stabilize the substrate (Stagg et al. 2016). Loss of migration resilience could be offset by removal of

levees to allow for lateral movement of the wetland, along with appropriate land acquisition and other site restoration actions. Other actions may be feasible.

In summary, in the spirit of Bayesian learning whereby predictions are improved by incorporating additional knowledge, our resilience prediction model is intended to be updated, and predictions enhanced, over time with new site data. As management activities change over time, they could be incorporated into the model or the model updated into a fuller, explicit decision structure.

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Author contributions BGM programmed the Bayesian network model, conducted statistical analyses of the case file data and tests of the model structures, and drafted the manuscript; KMT provided data for the case files and contributed to writing the manuscript. JAC provided data for the case files, and contributed to statistical analyses and writing the manuscript. GRG provided administrative support and contributed to writing the manuscript. All authors contributed to the evolutionary development of the model network influence structure.

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Data availability Research data and model structures are submitted as supplementary material. The Bayesian network model is available at <https://doi.org/10.59381/efgk0939>.

Declarations

Competing interests The authors declare no competing interests.

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References

- Aguilera PA, Fernández A, Fernández R, Rumi R, Salmerón A (2011) Bayesian networks in environmental modelling. *Environ Model Softw* 26(12):1376–1388
- Allen JRL (1997) Simulation models of salt-marsh morphodynamics: some implications for high-intertidal sediment couplets related to sea-level change. *Sed Geol* 113:211–223
- Allen CR, Birge HE, Angeler DG, Arnold CA, Chaffin VC, DeCaro DA, Garmestani AS, Gunderson L (2018) Quantifying uncertainty and trade-offs in resilience assessments. *Ecol Soc* 23(1):3
- Barbier EB, Hacker SD, Kennedy D, Koch EW, Stier AC, Silliman BR (2011) The value of estuarine and coastal ecosystem services. *Ecol Monogr* 81:169–193
- Berman M, Baztan J, Kofinas F, Vanderlinden J-P, Chouinard O, Huctin J-M, Kane A, Mazé C, Nikulkina I, Thomson K (2020) Adaptation to climate change in coastal communities: findings from seven sites on four continents. *Clim Change* 159:1–16
- Brophy LS, Ewald MJ (2017) Modeling sea level rise impacts to Oregon's tidal wetlands: Maps and prioritization tools to help plan for habitat conservation into the future. Prepared for MidCoast Watersheds Council, Newport, Oregon. Estuary Technical Group, Institute for Applied Ecology. Corvallis, Oregon. p 64
- Buffington KJ, Janousek CN, Dugger BD, Callaway JC, Schile-Beers LM, Sloane EB, Thorne KM (2021) Incorporation of uncertainty to improve projections of tidal wetland elevation and carbon accumulation with sea-level rise. *PLoS ONE* 16(10):e0256707
- Caffrey MA, Beavers RL, Hoffman CH (2018) Sea level rise and storm surge projections for the National Park Service. Natural Resource Report Series NPS/NRSS/NRR—2018/1648. National Park Service. p. 34
- Cahoon DR, Guntenspergen G (2010) Climate change, sea-level rise, and coastal wetlands. *Natl Wetlands Newsl* 32:8–12
- Cahoon DR, Lynch JC, Perez BC, Segura B, Holland RD, Stelly C, Stephenson G, Hensel P (2002) High-precision measurements of wetland sediment elevation: II. The rod surface elevation table. *J Sediment Res* 72(5):734–739
- Cahoon DR, Lynch JC, Roman CT, Schmit JP, Skidds DE (2018) Evaluating the relationship among wetland vertical development, elevation capital, sea-level rise, and tidal marsh sustainability. *Estuaries Coasts* 42:1–15
- Callaway JC, Borde AB, Diefenderfer HL, Parker VT, Rybczyk JM, Thom RM (2012a) Pacific coast tidal wetlands. In: Batzer DP, Baldwin AH (eds) *Wetland habitats of North America: ecology and conservation concerns*. University of California Press, Berkeley, pp 103–116

- Callaway JC, Borgnis EL, Turner RE, Milan CS (2012b) Carbon sequestration and sediment accretion in San Francisco Bay tidal wetlands. *Estuaries Coasts* 35:1163–1181
- Callaway JC, Cahoon DR, Lynch JC (2013) The surface elevation table–marker horizon method for measuring wetland accretion and elevation dynamics. In: DeLaune R, Reddy K, Richardson C, Megonigal J (eds) *Methods in biogeochemistry of wetlands*. 10. Wiley, Hoboken, pp 901–917
- Capdevila P, Stott I, Oliveras Menor I, Stouffer DB, Raimundo LG, White H, Barbour M, Salguero-Gómez R (2021) Reconciling resilience across ecological systems, species and subdisciplines. *J Ecol Environ* 109(9):3102–3113
- Carr JC, Guntenspergen GR, Lirwan M (2020) Modelling marsh-forest boundary transgression in response to storms and sea-level rise. *Geophys Res Lett*. <https://doi.org/10.1029/2020GL088998>
- Chillo V, Anand M, Ojeda RA (2011) Assessing the use of functional diversity as a measure of ecological resilience in arid rangelands. *Ecosystems* 14(7):1168–1177
- Chivoiu B, Osland MJ, Enwright NM, Thorne KM, Guntenspergen GR, Grace JB, Dale LL (2022) Potential landward migration of coastal wetlands in response to sea-level rise within estuarine drainage areas and coastal states of the conterminous United States. US Geol Surv Data Release. <https://doi.org/10.5066/P96D1J6Z>
- Darwiche A (2009) *Modeling and reasoning with bayesian networks*. Cambridge University Press, New York, p 560
- DeLaune RD, White JR (2012) Will coastal wetlands continue to sequester carbon in response to an increase in global sea level?: a case study of the rapidly subsiding Mississippi river deltaic plain. *Clim Change* 110(1–2):297–314
- Do CB, Batzoglu S (2008) What is the expectation maximization algorithm? *Nat Biotechnol* 26:897–899
- Donaldson L, Bennie JJ, Wilson RJ, Maclean IMD (2019) Quantifying resistance and resilience to local extinction for conservation prioritization. *Ecol Appl* 29(8):e01989
- Enwright NM, Griffith KT, Osland MJ (2016) Barriers to and opportunities for landward migration of coastal wetlands with sea-level rise. *Front Ecol Evol* 14(6):307–316
- Federal Geographic Data Committee (2013) *Classification of wetlands and deepwater habitats of the United States*, 2nd edn. Wetlands Subcommittee, Federal Geographic Data Committee and U.S. Fish and Wildlife Service, Washington
- Fenton N, Neil M (2012) *Risk assessment and decision analysis with bayesian networks*. CRC Press, Boca Raton, p 524
- Ferrier S, Harwood TD, Ware C, Hoskins AJ (2020) A globally applicable indicator of the capacity of terrestrial ecosystems to retain biological diversity under climate change: the bioclimatic ecosystem resilience index. *Ecol Indic* 117:106554
- Frazier MR, Reusser DA, Lee HII, McCoy LM, Brown C, Nelson W (2013) *User's guide and metadata for WestuRE: U.S. Pacific Coast estuary/watershed data and R tools*. U.S. EPA, Office of Research and Development, National Health and Environmental Effects Research Laboratory, Western Ecology Division. 41 pp
- Geselbracht L, Freeman K, Kelly E, Gordon DR, Putz FE (2011) Retrospective and prospective model simulations of sea level rise impacts on Gulf of Mexico coastal marshes and forests in Waccasassa Bay, Florida. *Clim Change* 107(1–2):35–57
- Grace JB (2023) Integrated analysis shows how the effects of extreme flooding events propagate through fish communities to impact amphibians. *J Anim Ecol* 92(6):1106–1109
- Grieger R, Capon SJ, Hadwen WL, Mackey B (2020) Between a bog and a hard place: a global review of climate change effects on coastal freshwater wetlands. *Clim Change* 163:161–179
- Griffiths BS, Philippot L (2013) Insights into the resistance and resilience of the soil microbial community. *FEMS Microbiol Rev* 37(2):112–129
- Gutierrez BT, Plant NG, Thieler ER (2011) A bayesian network to predict coastal vulnerability to sea level rise. *J Geophys Res Earth Surf*. <https://doi.org/10.1029/2010JF001891>
- Hessburg PF, Reynolds KM, Salter RB, Dickinson JD, Gaines WL, Harrod RJ (2013) *Landscape evaluation for restoration planning on the Okanogan-Wenatchee National Forest, USA*. Sustainability 5:805–840
- Hessburg PF, Churchill DJ, Larson AJ, Haugo RD, Miller C, Spies TA, North MP, Povak NA, Belote RT, Singleton PH, Gaines WL, Keane RE, Aplet GH, Stephens SL, Morgan P, Bisson PA, Rieman BE, Salter RB, Reeves GH (2015) Restoring fire-prone Inland Pacific landscapes: seven core principles. *Landscape Ecol* 30:1805–1835
- Holling CS (1973) Resilience and stability of ecological systems. *Annu Rev Ecol Syst* 4:1–23
- Holmquist JR, Brown LN, MacDonald GM (2021) Localized scenarios and latitudinal patterns of vertical and lateral resilience of tidal marshes to sea-level rise in the contiguous United States. *J Geophys Res Earth's Future*. <https://doi.org/10.1029/2020EF001804>
- Janousek CN, Thorne KM, Takekawa JY (2019) Vertical zonation and niche breadth of tidal marsh plants along the northeast Pacific Coast. *Estuaries Coasts* 42:85–98
- Kirwan ML, Guntenspergen GR (2010) Influence of tidal range on the stability of coastal marshland. *J Phys Res*. <https://doi.org/10.1029/2009JF001400>
- Kirwan M, Megonigal J (2013) Tidal wetland stability in the face of human impacts and sea-level rise. *Nature* 504:53–60
- Kirwan M, Temmerman S (2009) Coastal marsh response to historical and future sea-level acceleration. *Q Sci Rev* 28:1801–1808
- Kirwan ML, Guntenspergen GR, D'Alpaos A, Morris JT, Mudd SM, Temmerman S (2010) Limits on the adaptability of coastal marshes to rising sea level. *Geophys Res Lett*. <https://doi.org/10.1029/2010GL045489>
- Kirwan M, Temmerman S, Skeehan E, Guntenspergen GR, Fagherazzi S (2016) Overestimation of marsh vulnerability to sea level rise. *Nat Clim Change* 6:253–260
- Kjaerulff UB, Madsen AL (2007) *Bayesian networks and influence diagrams: a guide to construction and analysis*. Springer, New York, p 318
- Langston AK, Coleman DJ, Jung NW, Shawler JL, Smith AJ, Williams BL, Wittingham SS, Chambers RM, Perry JE, Kirwan ML (2022) The effect of marsh age on ecosystem function in a rapidly transgressing marsh. *Ecosystems* 25:252–264

- Linhoss AC, Kiker GA, Aiello-Lammens ME, Chu-Agor ML, Convertino M, Muñoz-Carpena R, Fischer R, Linkov I (2013) Decision analysis for species preservation under sea-level rise. *Ecol Model* 263:264–272
- Lyons JE, Kalasz KS, Breese G, Boal CW (2020) Resource allocation for coastal wetland management: confronting uncertainty about sea level rise. In: Runge MC, Converse SJ, Lyons JE, Smith DR (eds) *Structured decision making: case studies in natural resource management*. Johns Hopkins University Press, Baltimore, pp 108–123
- Maegonigal JP, Chapman S, Crooks S, Dijkstra P, Kirwan M, Langley A (2016) Impacts and effects of ocean warming on tidal marsh and tidal freshwater forest ecosystems. In: Laffoley D, Baxter JM (eds) *Explaining ocean warming: causes, scale, effects and consequences*. IUCN, Gland, pp 105–120
- Marcot BG (2012) Metrics for evaluating performance and uncertainty of bayesian network models. *Ecol Model* 230:50–62
- Marcot BG (2019) Chap. 16. Causal modeling and the role of expert knowledge. In: Brennan LA, Tri AN, Marcot BG (eds) *Quantitative analyses in wildlife science*. The Johns Hopkins University Press, Baltimore, pp 298–309
- Marcot BG (2021) The science and management of uncertainty: dealing with doubt in natural resource management. CRC Press, Taylor and Francis, Boca Raton, p 277
- Marcot BG, Hanea A (2021) What is an optimal value of k in k-fold cross-validation in discrete bayesian network analysis? *Comput Stat* 36(3):2009–2031
- McLeod E, Chmura GL, Bouillon S, Salm R, Björk M, Duarte CM, Lovelock CE, Schlesinger WH, Silliman BR (2011) A blueprint for blue carbon: toward an improved understanding of the role of vegetated coastal habitats in sequestering CO₂. *Front Ecol Environ* 9(10):552–560
- Morris JT, Edwards J, Crooks S, Reyes E (2012) Assessment of carbon sequestration potential in coastal wetlands. In: Lal R, Lorenz K, Huttel R, Schneider BU, von Braun J (eds) *Recarbonization of the biosphere: ecosystems and the global carbon cycle*. Springer, New York, pp 517–553
- NASEM (2019) Reproducibility and replicability in science. national academies of sciences, engineering, and medicine. The National Academies Press, Washington, p 256
- National Oceanic and Atmospheric Administration, Office for Coastal Management. “Regional (30-meter) C-CAP Regional Land Cover Data” Coastal Change Analysis Program (C-CAP) Regional Land Cover, conus 2016 land cover dataset. Charleston, SC: NOAA Office for Coastal Management. https://www.coast.noaa.gov/hpdata/raster1/landcover/bulkdownload/30m_lc/. Accessed August, 2021
- Neumann JE, Emanuel K, Ravela S, Ludwig L, Kirshen P, Bosma K, Martinich J (2015) Joint effects of storm surge and sea-level rise on US Coasts: new economic estimates of impacts, adaptation, and benefits of mitigation policy. *Clim Change* 129:337–349
- Nevermann H, AghaKouchak A, Shokri N (2023) Sea level rise implications on future inland migration of coastal wetlands. *Global Ecol Conserv* 43:e02421
- Osland MJ, Grace JB, Guntenspergen GR, Thorne KM, Carr JA, Feher LC (2019) Climatic controls on the distribution of foundation plant species in coastal wetlands of the conterminous United States: knowledge gaps and emerging research needs. *Estuaries Coasts* 42:1991–2003
- Osland MJ, Chivoiu B, Enwright NM, Thorne KM, Guntenspergen GR, Grace JB, Dale LL, Brooks W, Herold N, Day JW, Sklar FH, Swarzenzki CM (2022) Migration and transformation of coastal wetlands in response to rising seas. *Sci Adv*. <https://doi.org/10.1126/sciadv.abo5174>
- Pearl J (1988) *Probabilistic reasoning in intelligent systems: networks of plausible inference*. revised second printing, 1st edn. Morgan Kaufmann Publishers, San Mateo, p 552
- Peck EK, Wheatcroft RA, Brophy LS (2020) Controls on sediment accretion and blue carbon burial in tidal saline wetlands insights from the Oregon Coast, USA. *J Geophys Res: Biogeosci* 125:e2019JG005464
- Perks RJ, Bernie D, Lowe J, Neal R (2023) The influence of future weather pattern changes and projected sea-level rise on coastal flood impacts around the UK. *Clim Change* 176:25
- Raabe EA, Stumpf RP (2016) Expansion of tidal marsh in response to sea-level rise: Gulf Coast of Florida, USA. *Estuaries Coasts* 39:145–157
- Rachid G, Alameddine I, Najm MA, Qian S, El-Fadel M (2021) Dynamic bayesian networks to assess anthropogenic and climatic drivers of saltwater intrusion: a decision support tool toward improved management. *Integr Environ Assess Manag* 17(1):202–220
- Rogers K, Saintilan N, Copeland C (2012) Modelling wetland surface elevation dynamics and its application to forecasting the effects of sea-level rise on estuarine wetlands. *Ecol Model* 244:148–157
- Rosencranz JA, Thorne KM, Buffington KJ, Takekawa JY, Hechinger RF, Stewart TE, Ambrose RF, MacDonald GM, Holmgren MA, Crooks JA, Patton RT, Lafferty KD (2018) Sea-level rise, habitat loss, and potential extirpation of a salt marsh specialist bird in urbanized landscapes. *Ecol Evol* 8(16):8115–8125
- Ross MS, Stoffella SL, Vidales R, Meeder JF, Kadko DC, Scinto LJ, Subedi SC, Redwine JR (2022) Sea-level rise and the persistence of tree islands in coastal landscapes. *Ecosystems* 25(3):586–602
- Sahin O, Stewart RA, Faivre G, Ware D, Tomlinson R, Mackey B (2019) Spatial bayesian network for predicting sea level rise induced coastal erosion in a small Pacific Island. *J Environ Manage* 238:341–351
- Scheffer M, Carpenter SR (2003) Catastrophic regime shifts in ecosystems: linking theory to observation. *Trends Ecol Evol* 18(12):648–656
- Schibalski A, Körner K, Maier M, Jeltsch F, Schröder B (2018) Novel model coupling approach for resilience analysis of coastal plant communities. *Ecol Appl* 28(6):1640–1654
- Schibalski A, Kleyer M, Maier M, Schröder B (2022) Spatiotemporally explicit prediction of future ecosystem service provisioning in response to climate change, sea level rise, and adaptation strategies. *Ecosys Serv* 54:101414
- Schieder NW, Walters DC, Kirwan ML (2017) Massive upland to wetland conversion compensated for historical marsh loss in Chesapeake Bay, USA. *Estuaries Coasts* 41(4):940–951
- Sisco MR, Bosetti V, Weber EU (2017) When do extreme weather events generate attention to climate change? *Clim Change* 143(1–2):227–241

- Stagg CL, Krauss KW, Cahoon DR, Cormier N, Conner WH, Swarzenski CM (2016) Processes contributing to resilience of coastal wetlands to sea-level rise. *Ecosystems* 19(8):1445–1459
- Steinmuller HE, Foster TE, Boudreau P, Hinkle CR, Chambers LG (2020) Tipping points in the mangrove march: characterization of biogeochemical cycling along the mangrove–salt marsh ecotone. *Ecosystems* 23:417–434
- Swanson KM, Drexler JZ, Schoellhamer DH, Thorne KM, Casazza ML, Overton CT, Callaway JC, Takekawa JY (2014) Wetland accretion rate model of ecosystem resilience (WARMER) and its application to habitat sustainability for endangered species in the San Francisco estuary. *Estuaries Coasts* 37:476–492
- Sweet W, Hamlington BD, Kopp RE, Weaver CP, Barnard PL, Bekaert D, Brooks W, Craghan M, Dusek G, Frederikse T, Garner G, Genz AS, Krasting JP, Larour E, Marcy E, Marra JJ, Obeysekera J, Osler M, Pendleton M, Roman D, Schmied L, Veatch W, White KC, Zuzak C (2022) Global and regional sea level rise scenarios for the United States: up-dated mean projections and extreme water level probabilities along U.S. coastlines. NOAA Technical Report NOS 01. National Oceanic and Atmospheric Administration, National Ocean Service, Silver Spring, p 111
- Takekawa JY, Woo I, Spautz H, Nur N, Grenier JL, Malamud-Roam K, Norby JC, Cohen A, Malamud-Roam F, Wainwright-DeLa Cruz SE (2006) Environmental threats to tidal marsh vertebrates of the San Francisco Bay Estuary. *Stud Avian Biology* 32:176–197
- Tebaldi C, Strauss BH, Zervas CE (2012) Modelling sea level rise impacts on storm surges along US coasts. *Environ Res Lett*. <https://doi.org/10.1088/1748-9326/7/1/014032>
- Thorne KM, Takekawa JY, Elliott-Fisk DL (2012) Ecological effects of climate change on salt marsh wildlife: a case study from a highly urbanized estuary. *J Coastal Res* 28(6):1477–1487
- Thorne KM, Elliott-Fisk DL, Wylie GD, Perry WM, Takekawa JY (2013) Importance of biogeomorphic and spatial properties in assessing a tidal salt marsh vulnerability to sea-level rise. *Estuaries Coasts* 37:941–951
- Thorne KM, Buffington KJ, Elliott-Fisk DL, Takekawa JY (2015a) Tidal marsh susceptibility to sea-level rise: importance of local-scale models. *J Fish Wildl Manage* 6(2):290–304
- Thorne KM, Dugger BD, Buffington KJ, Freeman CM, Janousek CN, Powelson KW, Gutenspergen GR, Takekawa JY (2015b) Marshes to mudflats—Effects of sea-level rise on tidal marshes along a latitudinal gradient in the Pacific Northwest. *US Geol Surv Open-File Rep* 2015–1204. <https://doi.org/10.3133/ofr20151204>
- Thorne KM, MacDonald GM, Ambrose RF, Buffington KJ, Freeman CM, Janousek CN, Brown LN, Holmquist JR, Gutenspergen GR, Powelson KE, Barnard PL, Takekawa JY (2016) Effects of climate change on tidal marshes along a latitudinal gradient in California. *US Geol Surv Open-File Rep* 2016–1125. <https://doi.org/10.3133/ofr20161125>
- Thorne KM, MacDonald GM, Gutenspergen G, Ambrose R, Buffington K, Dugger B, Freeman C, Janousek C, Brown L, Rosencranz J, Holmquist J, Smol J, Hargan K, Takekawa J (2018) U.S. Pacific coastal wetland resilience and vulnerability to sea-level rise. *Sci Adv* 4(2):eaao3270
- Titus JG, Jones R, Streeter R (2008) Maps that depict site-specific scenarios for wetland accretion as sea level rises along the mid-atlantic coast. Section 2.2, EPA 430R07004. In: Titus JG, Strange EM (eds) Background documents supporting climate change science program synthesis and assessment product 4.1. U.S. Environmental Protection Agency, Washington, pp 176–186
- Wagener F (2020) Geometrical methods for analyzing the optimal management of tipping point dynamics. *Nat Resour Model* 33(3):e12258
- Webb EL, Friess DA, Krauss KW, Cahoon DR, Gutenspergen GR, Phelps J (2013) A global standard for monitoring coastal wetland vulnerability to accelerated sea-level rise. *Nat Clim Change* 3:458–465
- Wesner JS, Pomeranz JPF (2021) Choosing priors in bayesian ecological models by simulating from the prior predictive distribution. *Ecosphere* 12(9):e03739
- White EE Jr, Ury EA, Bernhardt ES, Yang X (2022) Climate change driving widespread loss of coastal forested wetlands throughout the north american coastal plain. *Ecosystems* 25:812–827
- Woodworth PL (2017) Differences between mean tide level and mean sea level. *J Geodesy* 91:69–90
- Zhao Q, Bai J, Huang L, Gu B, Lu Q, Gao Z (2016) A review of methodologies and success indicators for coastal wetland restoration. *Ecol Ind* 60:442–452
- Zhou Z-J, Hu C-H, Xu D-L, Yang J-B, Zhou D-H (2010) New model for system behavior prediction based on belief rule based systems. *Inf Sci* 180:4834–4864

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