Forecasting ecosystem services to guide coastal wetland rehabilitation decisions

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Abstract

Coastal wetlands provide diverse ecosystem services such as flood protection and recreational value. However, predicting changes in ecosystem service value from restoration or management is challenging because environmental systems are highly complex and uncertain. Furthermore, benefits are diverse and accrue over various timescales. We developed a generalizable mathematical coastal management model to compare restoration expenditures to ecosystem service benefits and apply it to McInnis Marsh, Marin County, California, USA. We find that benefits of restoration outweigh costs for a wide range of assumptions. For instance, costs of restoration range from 8–30% of the increase in ecosystem service value over 50 years depending on discount rate. Flood protection is the dominant monetized service for most payback periods and discount rates, but other services (e.g., recreation) dominate on shorter timescales (> 50% of total value for payback periods ≤4 years). We find that the range of total ecosystem service value is narrower than overall variability reported in the literature, supporting the use of mechanistic methods in decision-making around coastal resiliency. However, the magnitude and relative importance of ecosystem services are sensitive to payback period, discount rate and risk tolerance, demonstrating the importance of probabilistic decision analysis. This work provides a modular, transferrable tool to that can also inform coastal resiliency investments elsewhere.

Keywords

Ecosystem services; economic valuation; environmental modeling; coastal wetlands; climate adaptation; decision analysis

Declarations of Interest

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1. Introduction

Coastal wetlands are increasingly recognized as multifunctional environments that provide diverse services such as flood protection, urban water filtration and nesting and breeding habitat for key species (Aerts et al. 2014; Costanza et al. 2008; Yang et al. 2017). The hydrologic function of wetlands is the most widely cited, and reclamation and development of wetlands (particularly in flood plains) have greatly increased the magnitude of flood damages in the United States since colonial times (Acreman and Holden 2013; Hey and Philippi 1995). However, policy-makers and environmental interest groups are increasingly viewing wetland restoration and conservation as tools to preserve and enhance diverse ecological, recreational and other functions. For example, in the San Francisco Bay area, >85% of historical tidal marsh area has been diked, filled or otherwise lost, endangering populations of migratory birds who roost and forage there (USGS 2018). The benefits to these key species are commonly cited justifications for wetland restoration initiatives (e.g., South Bay Salt Pond Restoration Project 2015). Coastal wetlands therefore provide diverse services to diverse stakeholders, and these services accrue in different units over different timescales. This, together with the variability and uncertainty inherent in environmental systems, presents a challenge to decision-makers who must weigh these prospective future benefits against costs of restoration or preservation.

There exist multiple frameworks to calculate ecological value of land-use scenarios, but their utility in decision-making has been limited by narrow scope and poor support for prospective analysis. Grêt-Regamey et al. (2017) identify 68 unique ecosystem service valuation tools, of which the most comprehensive and widely cited is the *Integrated Valuation of Ecosystem Services and Tradeoffs* (*InVEST*) model (Sharp et al. 2018). These tools couple biophysical and economic models and can contribute to the policy process by estimating benefits associated with alternative land-use assumptions (Goldstein et al. 2012). However, existing tools tend to focus on a small subset of ecosystem services (de Groot et al. 2010; Grêt-Regamey et al. 2017) and mostly do not characterize the large parameter space characteristic of unknown, alternative states of complex environmental systems (Hamel and Bryant 2017). Conversely, wide variability in retrospective ecosystem service valuations has limited the utility of landcover-based benefits-transfer approaches. For example, in the case of wetlands, total ecosystem service value may range from < 2 \$ ha^{-1} yr^{-1} to > 340 000 \$ ha^{-1} yr^{-1} (2017-\$), depending on highly site-specific factors such as the value of avoided floods and the potential for conservation of vulnerable species (Brander et al. 2006). Overall, it has been poorly understood whether prospective ecosystem service models can narrow these uncertainties, and this has limited the interpretability of model outputs by decision-makers (Hamel and Bryant 2017).

Our previous work has demonstrated that controlling for uncertainties that are correlated across policy alternatives can substantially increase confidence in valuations of proposed interventions (Reichert and Borsuk 2005). Isolating uncertainties associated with hypothetical environmental changes from the baseline uncertainties inherent to environmental systems however requires that analysis be carried out within integrated probabilistic environments or “wrappers”, a facility not supported by commonly used off-the-shelf ecosystem service valuation tools (Hamel and Bryant 2017). Indeed, available tools tend to make uncertainty analysis a time-consuming process, and it is frequently neglected in practice: Seppelt et al. (2011) found that only one third of 460 studies carried out even basic uncertainty analysis. Emerging graphical methods known variously as “results chains” (Tallis et al. 2017), “logic models” (CDC 2010) and “Bayesian networks” (Pearl 1995) are well-suited to facilitate quantitative modeling that tracks correlations of uncertain variables. Previously, we have demonstrated how these techniques can be used to encode interacting biophysical pathways between environmental policy decisions and ecosystem services of relevance to stakeholders in terms of available data and modeling capacity (Borsuk et al. 2001; Borsuk et al. 2012; Mason and Olander 2018).

Recent updates to federal guidelines for environmental projects, risk management, and natural resource management require explicit characterization of ecosystem service value of policy alternatives (CEQ 2014; FEMA 2016; Olander et al. 2018; United States Forest Service 2012). Therefore, methods to improve forecasting and benefits modeling are urgently needed. Management of coastal wetlands presents a particularly important research area given increasing attention these environments are receiving internationally (Barbier 2013; Yang et al. 2017) and the poorly characterized conceptual gaps between biophysical conditions and socially valued outcomes (Boyd et al. 2015). We propose that structuring environmental policy questions within a Bayesian analytical framework has the potential to improve decision-making by narrowing and robustly assessing uncertainties. In particular, methods that track correlated uncertainties may provide a more robust quantification of benefits of policy alternatives in highly complex and variable environments such as coastal wetlands.

Here, we synthesize current scientific understanding of the biophysical pathways between coastal restoration and ecosystem service endpoints into a quantitative, probabilistic model. Using a case study from the San Francisco Bay area, California, USA, we evaluate how risk tolerance and discount rate interact with model uncertainties and non-stationarities to determine policy optima. This work can be easily transferred to other sites in the San Francisco Bay estuary, where ecosystem services are likely to be similar and where wetland restoration and conservation has become an environmental management priority (USGS 2018). More broadly, this work evaluates how mechanistically explicit models can inform decisions in the highly complex and uncertain setting of coastal wetlands. Finally, we argue that policy interpretability of counterfactual biophysical and economic model output is dependent on consideration of decision-analytic parameters such as discount rate, payback period and risk tolerance. This points to the importance of structuring such analysis within probabilistic, decision-analytic environments.

2. Methods

We present an analytic framework to reconcile uncertain future costs and ecosystem service benefits associated with alternative management decisions for coastal marsh environments. To capture the uncertainties in model formulations, we nest biophysical and economic models within a probabilistic Monte Carlo framework. In previous work, we developed general and site-specific conceptual models for ecosystem service impacts of coastal management interventions (Section 2.1). Here, we extend the site-specific conceptual model developed for the McInnis Marsh restoration project, Marin County, California, USA (Section 2.2), by replacing conceptual relationships with quantitative biophysical and economic models.

The modeling framework allows management scenarios to be compared in terms of probabilistically distributed future costs and benefits corresponding to (1) water quality improvements; (2) reduced rain-driven flooding; (3) improved recreational value; (4) enhanced species abundance; and (5) carbon sequestration, in comparison with recurring and upfront management costs (e.g., creek dredging). We quantify the impact of decision-maker preferences and values (e.g., payback period, discount rate) on economic valuations and explore the role these may have on decision-making.

2.1. <u>Conceptual model development</u>

In previous work, we developed a conceptual model for how potential management interventions in coastal wetland environments impact interrelated biophysical phenomena and how these biophysical phenomena control key ecosystem services (Mason et al. 2018). In collaboration with colleagues from the San Francisco National Estuarine Research Reserve (NERR), we then evaluated how this general framework could be adapted to site-specific settings using the case study of McInnis Marsh, a historic coastal marshland in Marin Co., California, USA, where land-use planning activities are ongoing (Section 2.2) (Mason and Olander 2018). Local interest and high public engagement in marshland restoration, a diversity of potential ecosystem services and several potential restoration plans make the McInnis Marsh system have made this site a good case study for development of a decision tool based on ecosystem services. We developed a conceptual model specific to McInnis Marsh, through meetings with expert stakeholders who have been involved in planning at McInnis Marsh. These stakeholders included ecologists, biologists, hydrologist and outreach specialists from the San Francisco NERR, a local conservation advocacy organization and a hydrology consulting firm retained by Marin County. The process of developing a site-specific conceptual model is described more thoroughly by Mason and Olander (2018).

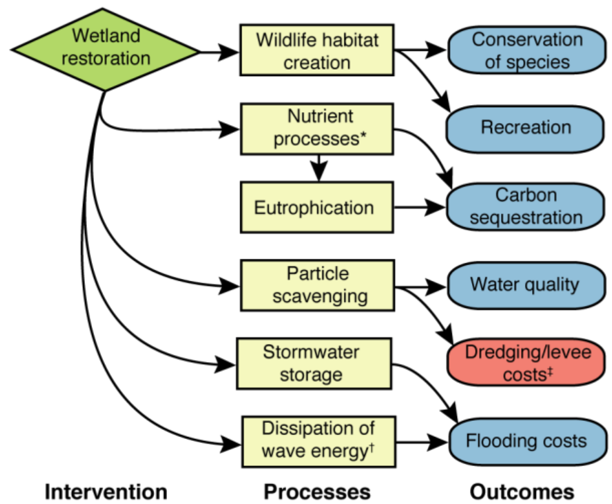

Figure 1: Ecosystem service outcomes of value to McInnis Marsh stakeholders with mediating biophysical processes affected by wetland restoration alternatives. *Principal nutrient removal processes are adsorption/plant uptake (physico-chemical) and denitrification (Vymazal 2007). [†]Risks from storm surges and risk abatement provided by McInnis Marsh restoration are assumed to be negligible. Outcomes include costs (‡) and benefits of interventions. To compare management scenarios (Section 2.2), we sum costs and benefits for each (Section 2.3). Conceptual model adapted from Mason and Olander (2018).

Stakeholders identified cost savings from dredging, water quality benefits, existence value, commercial fishing, aesthetic value, cultural value, recreational value, atmospheric carbon sequestration benefits, and flood-protection benefits. Further discussion and review of technical materials narrowed our focus on flood-protection benefits to protection against flooding driven by rain events (Kamman Hydrology & Engineering 2004). The ecosystem services quantified here and relevant biophysical mechanisms are represented in Figure 1.

2.2. <u>McInnis Marsh</u>

McInnis Marsh is a 180-acre complex of historic tidal wetlands adjacent to San Pablo Bay, bounded by Las Gallinas and Miller diked creeks, in San Rafael, Marin County, California, USA (Kamman Hydrology & Engineering 2016) (Figure 2). Construction of levees in the early 1900s progressively severed tidal and riparian connectivity and resulted in the loss of native vegetation (Kamman Hydrology & Engineering 2004). The complex is classified as “emergent herbaceous wetlands" by the National Land Cover Database (MRLC 2019) and is covered predominantly by nonnative grassland species such as ripgut brome (Kamman Hydrology & Engineering 2004). Surrounding landcover is predominantly low- and medium-intensity development, uninhabited grasslands and marshland and (MRLC 2019). Marin County has a warm-summer Mediterranean climate with wet winters and dry summers (Tang 2006). Local annual precipitation is projected to increase by 2–15% over the 21st century, while sea level rise (SLR) may range between 1.4–5.5 ft (ICF International 2015; Micheli et al. 2012), increasing risks of flooding to nearby areas.

We quantify benefits for three hypothetical management scenarios based on a simplified subset of potential restoration options identified in a recent feasibility study (Kamman Hydrology & Engineering 2016):

A. No action (present-day): maintain existing levees and infrastructure;
B. Riparian levee excavation: Gallinas creek is allowed to overflow into McInnis Marsh; and
C. Riparian and tidal levee excavation: same as "B", but with tidal connectivity restored.

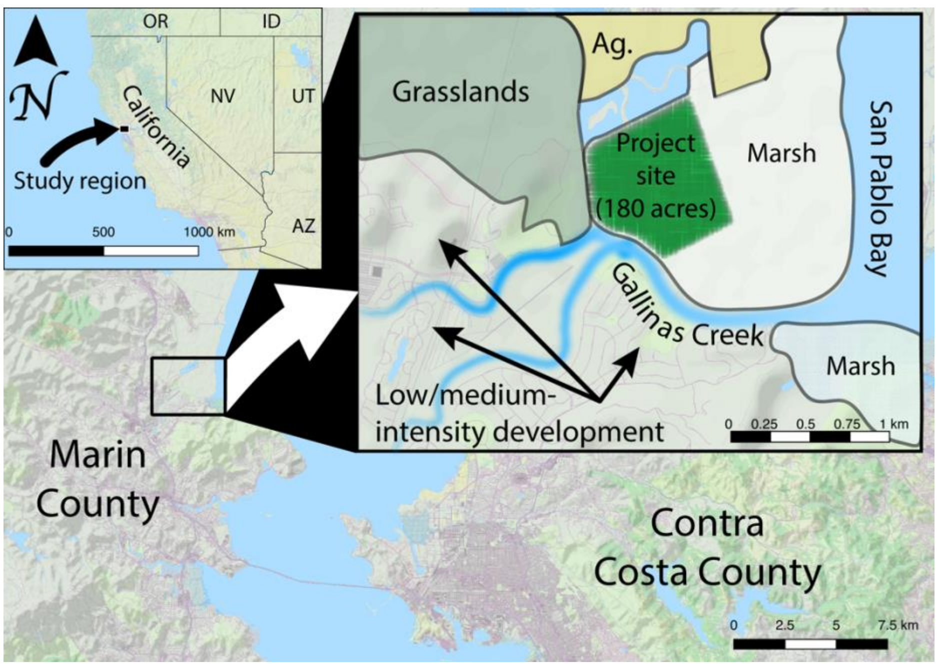

Figure 2: Map showing McInnis Marsh site and the North and South forks of Gallinas Creek with respect to prevailing land cover from the National Land Cover Database (MRLC 2019). Nearby low and medium intensity development is predominantly residential. Agricultural land ("Ag.") is used for oat-hay and dairy production (Marin Conservation League 2010). Created using QGIS (2018) with base map by Thunderforest (2018).

2.3. Mathematical model

The conceptual model is organized into a graphical analytical framework using Analytica (release 5.2.9.142) (Lumina Decision Systems 2019). This platform allows for graphical representation of interrelated variables with uncertain values. All model components and their mathematical representations are described in the following sections. We provide economic expressions of future and actual costs and benefits for each scenario. Economic valuations do not include expected benefits related to conservation of key species, for which no suitable site-specific economic assessment has been identified. We actualize all recurring costs and benefits for which a dollar-value is assigned and evaluate the impact of discount rate (ranging between 3 and 7%) (NCEE 2010) and cost horizon (0–80 years) on valuations. We convert all costs to 2017 U.S. dollars using the consumer price index (Sahr 2018).

Scenarios $k \in \{A, B, C\}$ are compared in terms of their actualized values P_k, which are the sums of economic costs and benefits over given payback periods and discount rates. That is, $P_k = \sum_m P_{k,m}$ where costs and benefits m correspond to flood risks (Section 2.4), water quality improvements (Section 2.5), recreational value (Section 2.6), carbon sequestration (Section 2.7) and sediment management costs (Section 2.8). We further compare scenarios in terms of their likely ability to increase abundance of several key species (Section 2.9) but this is not quantified economically.

2.4. Flood risk abatement

Tidal marsh restoration reduces flood risks by dissipating kinetic energy of incoming storm surges and providing storage volume to buffer tidal and pluvial flooding (Acreman and Holden 2013). The McInnis Marsh and adjacent wetlands abut the sheltered San Pablo Bay, and so flood risks are primarily related to inadequate evacuation of stormwater and the overtopping of diked creeks (U.S. ACE 2013). Rising sea levels are reducing the hydraulic gradient in Gallinas Creek, slowing evacuation of water and increasing the yearly probability of a storm event that overtops the dikes (Kamman Hydrology & Engineering 2004). A breach of the marsh-side dike in Scenarios ‘B’ and ‘C’ reduces these risks by providing extra water storage capacity from the creek.

We consider probabilistically distributed flood events based on recurrence intervals for water elevations in Gallinas Creek (Kamman Hydrology & Engineering 2016). Prior hydraulic analysis of this system described how these recurrence intervals change under different sea level rise scenarios (U.S. ACE 2013). We use this analysis to describe the probability of a flood event as a function of sea level rise which is itself probabilistically distributed and spans the range of outcomes under different scenarios proposed by the Intergovernmental Panel on Climate Change (IPCC) (Church et al. 2013). We calculate the economic damage of a flood event based on real estate sales data for Santa Venetia (Benson 2018; MarinMap 2018) and a probabilistically distributed damage factor (Dutta et al. 2003). While sea level rise increases risks of flood events with time, growth in population and/or long-term increases in property values will increase the economic impact of any flood event. To account for this, we consider an annualized population growth factor of 0.56% (State of California Department of Finance 2018).

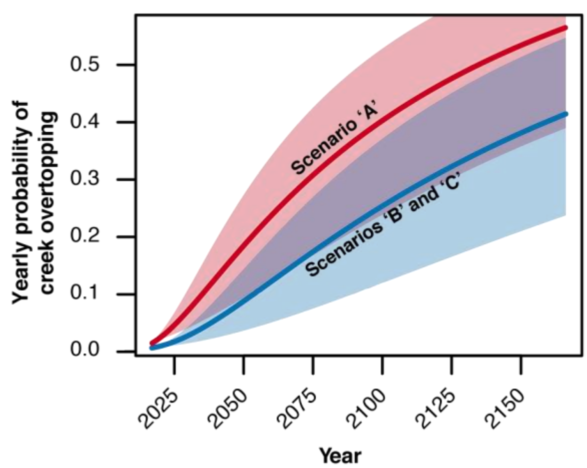

Figure 3: Annual probability of dike overtopping by scenario over time. Solid lines correspond to expected probability and shaded regions correspond to 90% confidence interval.

Table 1 presents a parameterization of the net present value (NPV) of future flood risks under different management scenarios. We consider a yearly probability of flood event (corresponding to dike overtopping) that increases with uncertain future sea level rise. For no-action Scenario A, we fit an inverse function to the relationship between log yearly probability of occurrence and corresponding water surface elevations in Gallinas Creek (asymptotic at log-probability = 0 or probability = 1) (Kamman Hydrology & Engineering 2016; 2013). We include an offset term to account for sea level rise, which makes successively higher water elevations more probable. At present-day, a dike-overtopping event has a yearly probability of roughly 2%, increasing to 28% (90% CI: 15%–39%) within 50 years depending on realized average sea level rise, consistent with previous analyses (Kamman Hydrology & Engineering 2016). To approximate the benefits of breaching the levees to the McInnis Marsh restoration area, we consider the additional water storage provided and scale floodwater levels in the channel according to $h_2 = \left(w_1\, h_1 + L(w_2 - w_1)\right)/w_2$ for $h_2 > L$ and $h_2 = h_1$ for $h_2 \leq L$ where w_1 is the average width of the creek (150 ft) and w_2 is the average width of the marsh perpendicular to the creek, L is the elevation of the marsh platform and h_1 and h_2 are maximum yearly water elevations under no-breach (Scenario 'A') and breach (Scenarios 'B' and 'C') respectively (Kamman Hydrology & Engineering 2004; 2016). We fit rescaled surface elevations to an inverse distribution. The parameterization retained for water surface elevation after implementing a breach to Gallinas Creek suggests annual flood risk under the restoration scenarios would be reduced to 0.5% per year, rising to 15% (90% CI: 6–24%) within 50 years (Figure 3).

Table 1: Net present value of future flood risks at McInnis Marsh, calculated as a function of local real estate value and probability of dike overtopping in hypothetical management scenarios

Parameter[a]	**Units**[b]	**Description**	**Reference**
$P_{flood} = -\int_{t=2017}^{t=T} \frac{V \times F(t) \times (1+g)^{t-2017}}{(1+r)^{t-2017}} dt$	\$	Net present value of future floods	
$V = \sum_{i=1}^{4} d_i n_i v_i$	\$	Value of flood event	
$d_i = \begin{cases} Exp(6.5) & i \in \{1,2,3\} \\ Exp(7.6) & i = 4 \end{cases}$		Damage factor[c]	Dutta et al. (2003)
$i = \begin{cases} 1 \rightarrow & \text{res., single family} \\ 2 \rightarrow & \text{res., single family, improved} \\ 3 \rightarrow & \text{res., mult. family} \\ 4 \rightarrow & \text{commercial} \end{cases}$		Types of property affected	Benson (2018)
$n_i = \begin{cases} 13 & i = 1 \\ 416 & i = 2 \\ 5 & i = 3 \\ 24 & i = 4 \end{cases}$		Number of each type of property in the Santa Venetia community	MarinMap (2018)
$v_i = \begin{cases} 975\,000 & i = 1 \\ 1\,271\,000 & i = 2 \\ 1\,254\,000 & i = 3 \\ 4\,547\,000 & i = 4 \end{cases}$	\$	Value of each property type	Benson (2018)
$F(t) = \begin{cases} e^{2.1/\left(-0.5-\frac{s}{304}\times(t-2017)\right)} & Scen.'A' \\ e^{3.4/\left(-0.6-\frac{s}{304}\times(t-2017)\right)} & Scen.'B','C' \end{cases}$		Yearly probability of flood (dike overtopping)	
$s \sim N(6.9, 2.1)$	mm yr^{-1}	Average sea level rise[d]	Church et al. (2013)
$g = 0.56\%$		Annualized population growth rate 2011–27	State of California Department of Finance (2018)

[a] Normal distribution represented as $N(\mu, \sigma.)$; exponential distribution represented as $Ex(\lambda)$; *'A', 'B' and 'C'* refer to hypothetical management interventions. We consider a discount rate *r* ranging from 3–7%.
[b] All dollar values are expressed in terms of 2017-\$.
[c] Considering a 1-m flood event as the 99th percentile.
[d] Based on the 95% confidence interval of sea level rise from 2013–2100 across RCP2.6–RCP2.8 ICPP scenarios.

2.5. Water quality improvements

Coastal wetlands scavenge nitrogen (N) and phosphorus (P) from freshwater inputs (notably urban stormwater), reducing primary biological productivity and risks of eutrophication in receiving waters (Jing et al. 2001). Recent economic valuation suggests that, together, N and P discharges account for >99% of the economic value of municipal water quality impacts (Hernandez-Sancho et al. 2010). We consider this likely to extend to urban stormwater, given the similar ratio of nutrients, metals, coliforms and other contaminants (Brouillette 2001; Novotny and Olem 1994). The economic value of these avoided inputs depends on site-specific factors such as the biophysical response of receiving waters to incremental concentrations of nutrients, the economic uses and value of receiving waters and prices of relevant technological alternatives (e.g., investments in wastewater treatment capacity) (Compton et al. 2011; Hernandez-Sancho et al. 2010; Yang et al. 2008).

We have not identified any regionally relevant models to evaluate economic value of water quality benefits from coastal wetland rehabilitation. We therefore use a benefits-transfer method to apply economic valuations derived elsewhere, scaling economic value according to the likely magnitude of the benefit provided. Such ‘function transfers’ have the advantage of aggregating data based on a variety of underlying economic valuation methods but require attention to avoid generalization error (the inclusion of valuations from incomparable sites) (Boutwell and Westra 2013). We 1) review the literature for economic valuations of avoided N and P discharges to receiving waters, 2) evaluate the underlying for similarities and differences to the case studied here and; and 3) evaluate the likely magnitude of the benefit here by scaling previous estimates by mass of N and P retained. Most data identified derive from estimates of municipal wastewater treatment. We follow previous authors (Russell et al. 2013; Widney et al. 2017) in using such data as a proxy for valuation of ecosystem services of natural environments.

Gren (1995) calculated average surface water quality benefits of roughly $110\ \$\ \mathrm{kg}^{-1}$ N (2017-\$) for wetlands in Sweden. This is consistent with the upper range of shadow prices of $10–100\ \$\ \mathrm{kg}^{-1}$ N and $10–150\ \$\ \mathrm{kg}^{-1}$ P (2017-\$) calculated from investments in wastewater treatment in Spain, also for discharges to surface water (Hernandez-Sancho et al. 2010). Meanwhile, a review by Compton et al. (2011) found damage and abatement costs respectively in the ranges $0–61\ \$\ \mathrm{kg}^{-1}$ N and $3–105\ \$\ \mathrm{kg\ N}^{-1}$ (2017-\$) in the setting of Chesapeake Bay, Maryland, USA. Hopkins et al. (2018) described per-kg treatment costs that decrease approximately logarithmically for increasing concentrations of N, ranging from approximately $12\ \$\ \mathrm{kg}^{-1}$ for $7.5\ \mathrm{mg\ L}^{-1}$ to $250\ \$\ \mathrm{kg}^{-1}$ for $3.9\ \mathrm{mg\ L}^{-1}$ (2017-\$). The Cape Cod Commission (2013) identified treatment costs in the range $659–1{,}896\ \$\ \mathrm{kg}^{-1}$ N (2017-\$) for household-to-community-scale treatment technologies, inclusive of significant labor and maintenance expenses. There, the relevant endpoint was impacts on groundwater resources widely used as drinking water and where there has been widespread wastewater contamination (Schaider et al. 2016). We therefore exclude this last reference from our quantification of benefits of N removal. As discussed in the results (Section 3.2), assumptions for water quality valuation have a small impact on overall ecosystem service valuation. We therefore consider uniformly distributed potential benefits of $0–250\ \$\ \mathrm{kg}^{-1}$ N and $10–150\ \$\ \mathrm{kg}^{-1}$ P (2017-\$). We consider the NPV of removed N and P as a function of discount rate and cost horizon.

We model future P and N removal efficiencies for restoration scenarios as probability distributions based on a recent meta-analysis of 203 freshwater wetlands worldwide (Land et al. 2016). Available data suggest this is a conservative proxy for tidal wetlands (Li et al. 2015). N removal efficiency was strongly negatively correlated with hydraulic loading rate (HLR). We use the relationships between HLR and nutrient removal efficiency from Land et al. (2016) to calculate hypothetical future removal efficiency at McInnis Marsh as a function of hypothetical future HLR under Scenarios ‘B’ and ‘C’. We consider HLR = $44.5\ \mathrm{L\ m}^{-2}\ \mathrm{day}^{-1}$ based on daily average flow in Gallinas Creek for the period January to July 2003 and 2004, assuming the surface area of the marsh area participates in nutrient scavenging. At this HLR, the relationship from Land et al. (2016) suggests an uncertain N removal efficiency with $\mu = 5.6\%$, $\sigma = 20\%$. Trends for P removal efficiency were inconsistent, and we therefore consider the observed distribution for all sites ($\mu = 44\%$, $\sigma = 38\%$). We consider present-day seasonal-average N and P (as dissolved inorganic phosphates) concentrations in incoming surface water at 1.3 mg L^{-1} and 0.4 mg L^{-1} based on residential runoff in San Francisco Bay watersheds (Novick and Senn 2014).

2.6. Recreational value

Worldwide, recreational and amenity uses represent the largest single share of total wetland ecosystem service value, accounting for roughly 30% of the total (Brander et al. 2006). We quantify potential future recreational value of a restored McInnis Marsh based on the value to birders, pedestrians, cyclists and dog owners.

We make inferences about the likely future number of visitors to a restored McInnis Marsh from publicly available data for the nearby China Camp State Park (Alta Planning + Design 2011). China Camp is roughly eight times the size of the McInnis Marsh site. We therefore consider it highly likely that a restored McInnis Marsh site would accommodate fewer annual visitors than China Camp at present day. As a central estimate for future visitation at McInnis Marsh by pedestrians, cyclists and dog owners, we scale annual visitation to China Camp by these groups according to surface area, and we consider that this estimate can vary by ±100%. We estimate the local population of birders in Marin County as being proportional to the population of birders in California as a whole (Carver 2013; United States Census Bureau 2018). We assume that the average number of visits per birder per year may be anything between 0 and 2 (uniform distribution). We have identified an economic value ranging from \$5.64 to \$7.63 (2017-\$) per visit based on guidelines by the U.S. Army Corps of Engineers (U.S. ACE 2016). This economic valuation was intended to be nationally representative and may underestimate values in the San Francisco Bay Area, where price parity is roughly 28% higher than the U.S. average (U.S. BEA 2019). We therefore multiply this range by a factor of 1.28 to reflect purchase parity in the San Francisco Bay Area. We include a mathematical derivation of this approach in showing parameterization of NPV in Table 2.

Table 2: Net present value of recreational value at McInnis Marsh calculated for hypothetical management scenarios

Parameter[a]	Units[b]	Description	Reference
$P_{recreation} = \int_{t=2017}^{t=T} \frac{N \times p \times (1+g)^{t-2017}}{(1+r)^{t-2017}} dt$	$	Present value of future recreation benefits	
$N = \begin{cases} 0 & Scen.\ 'A' \\ N_{birder} + N_{other} & Scen.\ 'B', 'C' \end{cases}$		Annual number of visits by birders and others[c]	
$N_{birder} = B_{Marin} \times U(0,2)$	visits year^{-1}	Number of birder visits per year	
$B_{Marin} = C_{Marin} \times \frac{B_{CA}}{C_{CA}}$	persons	Birder population of Marin County	
$C_{Marin} = 263\ 262$	persons	Total population of Marin County in 2017	State of California Department of Finance (2018)
$B_{CA} = 38\ 234\ 391$	persons	Total population of California in 2013	Idem
$C_{CA} = 4\ 864\ 000$	persons	Birder population of California in 2013	Carver (2013)
$N_{other} = N_{China\ Camp} \times R \times U(0,1)$	visits year^{-1}	Annual number of visits by people other than birders[c]	
$N_{China\ Camp} \sim U(67\ 680, 90\ 240)$	visits year^{-1}	Annual number of visits by people other than birders at China Camp[d]	Alta Planning + Design (2011)
$R = \frac{180}{1{,}514} = 0.12$		Ratio between McInnis Marsh and China Camp surface areas	Alta Planning + Design (2011); Kamman Hydrology & Engineering (2016)
$p \sim U(5.64, 7.63) \times f$	$ visit^{-1}	Value of each visit[c]	U.S. ACE (2016)
$f = 1.28$			U.S. BEA (2019)
$g = 0.56\%$		Annualized population growth rate in Marin County, 2011–27	State of California Department of Finance (2018)

[a] Normal distribution represented as *N(μ, σ.);* uniform distribution represented as *U(min, max)*. *'A', 'B' and 'C'* refer to hypothetical management interventions. We consider a discount rate *r* ranging from 3–7% as described in the text.

[b] All dollar values are expressed in terms of 2017-$.

[c] Range corresponding to 26–42 usage points based on presence of several general activities, alternative recreational opportunities within 30 minutes, basic facilities, good access and average aesthetic quality.

[d] 'Other' visits by pedestrians, cyclists and dog owners. Calculated by scaling annual visitation across all Marin County preserves (2,820,000–3,760,000) by proportion of visits accounted for by China Camp (5.4%) within a representative sample of 44% of Marin County parks (i.e., 5.4% of 1,240,800–1,654,400 annual visitors) (Alta Planning + Design 2011).

2.7. Carbon sequestration

Wetlands provide significant carbon storage benefits, which can potentially generate carbon credits (Callaway et al. 2012). In general, high and low marsh types have greater carbon storage potential than mid marsh and the relative surface areas of these types are a function of management intervention. We quantify the annual carbon storage potential at McInnis Marsh using carbon sequestration rates for different marsh types at the nearby China Camp State Park (Callaway et al. 2012). We retain probabilistically distributed values for carbon sequestration rates using the mean and standard error of measurements by marsh type at nearby China Camp State Park, pooled across ^{137}Cs and ^{210}Pb analytical methods. Both methods allow for accretion rates to be measured in soil cores. ^{137}Cs is a thermonuclear decay product first deposited worldwide in detectable amounts as of the early 1950s. Conversely, ^{210}Pb is a decay product of naturally occurring ^{226}Rn deposited in roughly constant amounts over time and whose concentration declines with depth according to (calculated) burial and (known) decay rates (He and Walling 1997). We consider normal distributions for high ($\mu = 889$ $\sigma = 256$ kg ha^{-1} yr^{-1}), mid ($\mu = 759$, $\sigma = 66$ kg ha^{-1} yr^{-1}) and low ($\mu = 1{,}189$ $\sigma = 338$ kg ha^{-1} yr^{-1}) marsh. The surface areas of each marsh type in each management intervention are summarized in Table 3. We consider a discount-rate-adjusted social cost of carbon (SCC, 2010-$ tonne^{-1}) equal to $1/(r + 0.002)$ where r is growth-corrected discount rate (e.g., 31 $ tonne^{-1} at $r = 3\%$) following Nordhaus (2017), converted to 2017-$ to be consistent with the broader analysis. We note that these benefits accrue globally and are not specific to the immediate vicinity of the site under consideration. Table 4 summarizes the parameterization of the NPV of future carbon sequestration potential for each management scenario.

Table 3: Net present value of future carbon sequestration in hypothetical management scenarios[a]

Parameter	Units	Description	Reference
$A_1 = \begin{cases} 60.5 + \frac{s}{304} \times 46.4 & Scen.'A' \\ 74.5 + \frac{s}{304} \times 46.4 & Scen.'B' \\ 75.8 + \frac{s}{304} \times 46.4 & Scen.'C' \end{cases}$	ha	Low marsh[b,c]	Kamman Hydrology & Engineering (2016)
$s \sim N(6.9, 2.1)$	mm yr^{-1}	Average sea level rise[d]	Church et al. (2013)
$A_2 = 129.3 - \frac{s}{304} \times 38.6$	ha	Mid marsh	Kamman Hydrology & Engineering (2016)
$A_3 = \begin{cases} 19.3 - \frac{s}{304} \times 4.9 & Scen.'A' \\ 5.3 - \frac{s}{304} \times 4.9 & Scen.'B' \\ 5.3 - \frac{s}{304} \times 4.9 & Scen.'C' \end{cases}$	ha	High marsh[c]	Kamman Hydrology & Engineering (2016)

[a] Hypothetical management interventions impact landcover beyond the 180-acre restoration area, and those areas are included here.
[b] Levee removal results in 14 ha of upland being converted to tidal wetland (low marsh). Low marsh includes mudflats.
[c] Restoring tidal connectivity results in 1.3 ha of upland being converted to tidal wetland (low marsh)
[d] Based on the 95% confidence interval of sea level rise from 2013–2100 across RCP2.6–RCP2.8 ICPP scenarios.

Table 4: Net present value of future carbon sequestration in hypothetical management scenarios

Parameter[a]	Units[b]	Description	Reference
$P_{carbon} = \int_{t=2017}^{t=T} \frac{S \times p}{(1+r)^{t-2017}} dt$	\$	Social value of carbon storage	
$S = \frac{1\ tonne}{1000\ kg} \sum_{i=1}^{4} s_i A_i$	tonne yr^{-1}	Yearly carbon sequestration of site[c]	
$s_i = \begin{cases} N(1\,189, 338) & i = 1 \\ N(759, 66) & i = 2 \\ N(889, 256) & i = 3 \\ 0 & i = 4 \end{cases}$	kg ha^{-1} yr^{-1}	Carbon storage capacity by marsh type	Callaway et al. (2012)
$i = \begin{cases} 1 \rightarrow & \text{Low marsh} \\ 2 \rightarrow & \text{Mid marsh} \\ 3 \rightarrow & \text{High marsh} \\ 4 \rightarrow & \text{Other marsh} \end{cases}$		Types of marsh	Veloz et al. (2014)
$p = \frac{1}{r + 0.002} R_{2010}$	\$ $tonne^{-1}$	Social cost of carbon	Nordhaus (2017)
$R_{2010} = 1.12$	\$-2017: \$-2010	Consumer price index inflation from 2010–17	Sahr (2018)

[a] Normal distribution represented as $N(\mu, \sigma.)$. We consider a discount rate r ranging from 3–7% as described in the text.
[b] Dollar values are expressed in terms of 2017-\$ unless otherwise stated.
[c] See Table 3for marsh areas A_i by management intervention.

2.8. Sediment management costs

Management of engineered wetlands involves significant investments in sediment control. Maintaining artificial channels requires levee construction and maintenance and periodic dredging of alluvial sediments, while levee breaches may involve removal and disposal of soils. To compare sediment management costs across scenarios at Gallinas Creek, we consider recurring annual dredging costs and upfront levee removal costs.

Annual dredging costs for the no-change Scenario ‘A’ are modeled as a normal distribution with mean and standard deviation derived from historical data (Leventhal 2015). Upfront levee removal costs for intervention Scenarios ‘B’ and ‘C’ are estimated from the costs of similar sites and scaled according to levee length. Table 5 presents a mathematical derivation of the NPV of these costs.

Table 5: Net present value of future dredging costs at McInnis Marsh in hypothetical management scenarios

Parameter[a]	**Units**[b]	**Description**	**Reference**
$P_{soil} = P_{levee} + P_{dredging}$	\$	Total present cost of levee removal and dredging	
$P_{levee} = -L \times p_{levee}$	\$ year^{-1}	Upfront cost of levee removal	
$L = \begin{cases} 0 & Scen.'A' \\ 1.77 & Scen.'B' \\ 2.74 & Scen.'C' \end{cases}$	km	Length of levee to be removed	Kamman Hydrology & Engineering (2016)
$p_{levee} \sim U(8.5, 17.0) \times 10^6$	\$ km^{-1}	Unit cost of levee removal and soil disposal[d]	CA DWR (2012)
$P_{dredging} = -\int_{t=2017}^{t=T} \frac{V \times p}{(1+r)^{t-2017}} dt$	\$	Present cost of recurring future dredging	
$V = \begin{cases} 40\ 063 & Scen.'A' \\ 33\ 640 & Scen.'B' \\ 15\ 291 & Scen.'C' \end{cases}$	m^3 year^{-1}	Dredging quantity under each scenario	Kamman Hydrology & Engineering (2016)
$p \sim N(26.16, 7.50)$	\$ m^{-3}	Average unit cost of dredging[c]	Leventhal (2015)

[a] Normal distribution represented as *N(μ, σ.);* uniform distribution represented as *U(min, max); ‘A’, ‘B’ and ‘C’* refer to hypothetical management interventions. We consider a discount rate *r* ranging from 3–7% as described in the text.
[b] All dollar values are expressed in terms of 2017-\$.
[c] Modeled based on mean and standard error of historical unit dredging costs.
[d] Converted from 2012-\$ mile^{-1}

2.9. Species abundance in marsh

In the San Francisco Bay Estuary, tidal marsh is an important habitat for water bird species including California black rail (*Laterallus jamaicensis coturniculus*), Ridgway's rail (*Rallus obsoletus*), and tidal marsh song sparrow (*Melospiza melodia*) (Mason and Olander 2018). We consider the impact of management interventions on creation of habitat for these water birds. The water bird population in our model was calculated as a function of species density multiplied by habitat area, where habitat area is determined by management interventions and environmental parameters. Present-day bird density and habitat area was obtained from the Future San Francisco Bay Tidal Marshes (Stralberg et al. 2011; Veloz et al. 2014). We assume a uniform distribution for bird density based on the local observed data: Ridgway's rail ranges from 0 to 3.3 birds ha^{-1}; black rail: 0 to 2.4 birds ha^{-1}; and song sparrow: 6.9 to 13.9 birds ha^{-1}. The resolution of these data allow them to be applied to individual marshland types within the McInnis Marsh complex, which together spans multiple grid cells.

We consider that density of Ridgway's rail increases by 25% when channel density is increased to between 50–150 m ha^{-1} (e.g., when a breach is constructed in Scenarios 'B' and 'C') following Spautz et al. (2006). We consider that black rail density increases by 5% as function of increased proportion of tidal marsh and increased cover of salt grass, common tule and bulrush in Scenario 'C' where tidal connectivity is restored and that song sparrow density increases by 14% in Scenario 'C' where density of Coyote brush, gumplant, rushes and ponds is greater (Spautz et al. 2006). For Ridgway's rail, black rail and song sparrow, we also consider that population is proportional to total habitat area, which increases by 14.16 ha and 62.72 ha respectively in Scenarios 'B' and 'C' (Kamman Hydrology & Engineering 2016). The salt marsh harvest mouse (*Reithrodontomys raviventris*) is an endangered species endemic to San Francisco Bay area salt marshes, with present-day species density of 18.9 ± 2.5 mice ha^{-1} (Sustaita et al. 2011). We account for how the local population may respond to increased habitat area (14.16 ha and 62.72 ha respectively in Scenarios 'B' and 'C') (Kamman Hydrology & Engineering 2016). Table 6 summarizes these estimates. While no direct economic benefit of harvest mice has been identified, they serve as prey for birds and land mammals (Konishi 2003). We quantify the economic value of birding in Section 2.6.

Table 6: Species persistence in McInnis Marsh under hypothetical management scenarios

Parameter[a]	**Units**	**Description**	**Reference**
$P_i = d_i \times h_i$	number of individuals	Population of each animal under consideration[b]	
$i = \begin{cases} 1 \rightarrow & black\ rail \\ 2 \rightarrow & Ridgway's\ rail \\ 3 \rightarrow & song\ sparrow \\ 4 \rightarrow & harvest\ mouse \end{cases}$		Species considered	
$d_1 = \begin{cases} U(0,2.4) & Scen.\ 'A','B' \\ U(0,2.4) \times 1.05 & Scen.'C' \end{cases}$	individuals ha^{-1}	Density of black rail	Spautz et al. (2006), Veloz et al. (2014)
$d_2 = \begin{cases} U(0,3.3) & Scen.'A' \\ U(0,3.3) \times 1.25 & Scen.'B','C' \end{cases}$	individuals ha^{-1}	Density of Ridgway's rail	Idem
$d_3 = \begin{cases} U(6.9,13.9) & Scen.'A' \\ U(6.9,13.9) \times 1.145 & Scen.'B','C' \end{cases}$	individuals ha^{-1}	Density of song sparrow	Idem
$d_4 = N(18.9,2.5)$	individuals ha^{-1}	Density of harvest mouse	Sustaita et al. (2011)
$h_i = \begin{cases} 6.75 & Scen.'A' \\ 20.91 & Scen.'B' \\ 69.47 & Scen.'C' \end{cases} \quad i \in \{1,2,3\}$	ha	Habitat area for species	Kamman Hydrology & Engineering (2016)
$h_4 = \begin{cases} 3.18 & Scen.'A' \\ 17.34 & Scen.'B' \\ 65.9 & Scen.'C' \end{cases}$	ha	Habitat area of harvest mouse	Idem

[a] Normal distribution represented as *N(μ, σ.);* uniform distribution represented as *U(min, max). 'A', 'B' and 'C'* refer to hypothetical management interventions.
[b] This analysis considers black rail, Ridgway's rail, song sparrow and harvest mouse.

3. Results

Overall, the ecosystem service valuation demonstrates that marsh restoration is likely to be more effective over time than maintaining the status quo, and this is primarily attributable to reduced flood risks (Section 3.1). The payback period required for restoration to be cost-effective is generally under 18 years, and this is not sensitive to assumptions regarding discount rate. Monte Carlo analysis reveals that, for lower-probability ($\leq 25^{th}$ percentile) outcomes of the future costs of flooding and the risk avoided by restoration, cost-effectiveness depends on an assumption of lower discount rates (Figure 4).

Restoration Scenarios 'B' and 'C' differ in terms of tidal connectivity, which affects the size of each type of marshland created or restored, leading to carbon sequestration benefits (Section 2.7) and the size of the habitats for certain key species (Section 2.9). However, of these, only carbon sequestration is valued economically in this framework, and this benefit is small (Section 3.4). Therefore, in terms of the characteristics of the economic analysis, Scenarios 'B' and 'C' are almost equivalent, and we confine our contrasts to no-action Scenario 'A' and the restoration Scenario 'C'.

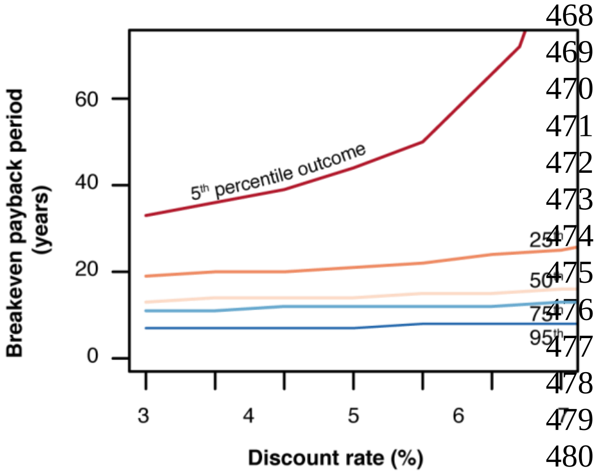

Figure 5: Break-even payback period as a function of discount rate for 5th, 25th, 50th (median), 75th and 95th percentiles of the distribution of ΔNPV between rehabilitation Scenario 'C' and no-action Scenario 'A'.

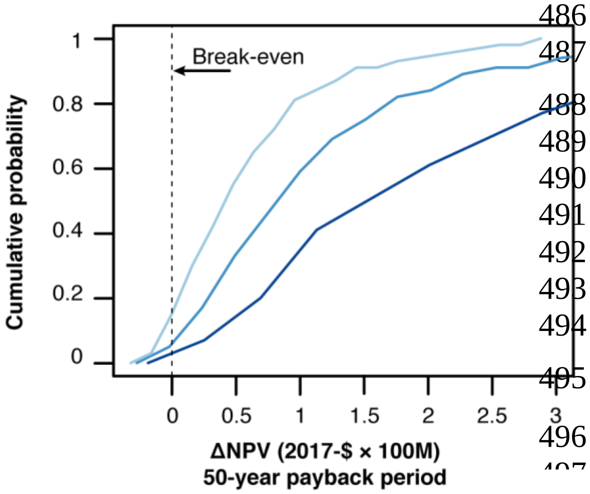

Figure 4: Cumulative probability distribution for the difference in the magnitude of the net present value (ΔNPV) between restoration Scenario 'C' and no-action Scenario 'A' for three discount rates, *r* assuming a payback period of 50 years.

While there is substantial uncertainty in the magnitude of net benefits of marsh restoration, the likely range of ecosystem service values calculated here is narrower than overall variability in the ecosystem service value of wetlands reported by Brander et al. (2006). For example, the 90% confidence interval for the difference in expected NPV between restoration Scenario 'C' and no-action Scenario 'A' (ΔNPV) over a 50-year payback period ranges from \$20.5M to \$585.7M at a 3% discount rate (Figure 5), or 5,616–160,411 \$ ha^{-1} $year^{-1}$ (mean = \$56,110 ha^{-1} $year^{-1}$) compared to the range of < 2 \$ ha^{-1} yr^{-1} to >340,000 \$ ha^{-1} yr^{-1} (2017-\$) reported by Brander et al. (2006). It should be noted that this is only a range of mean estimates across sites and does not reflect within-site uncertainties, which further increase this range.

The magnitude of the difference in NPV between restoration scenarios and the no-action scenario is highly dependent on the discount rate retained, because a substantial part of the benefits of restoration derive from flood protection, and the risks of flooding increase with time (Section 3.1).

3.1. Flood risks

Avoided flood risks represent the dominant ecosystem service of restoration scenarios over all horizons for which restoration is economically viable (>18 years; Figure 4), representing >73% of the difference in net present value between no-action Scenario 'A' and restoration Scenarios 'B' and 'C'. For instance, over a 50-year payback period, avoided floods account for 86–90% of total valued ecosystem services of marsh restoration for the 50th percentile simulation, ranging from \$74M (90% CI: \$6.3M–\$210M) at a 7% discount rate to \$200M (90% CI: \$18M–\$590M) at a 3% discount rate (Figure 6).

The value of avoided flood risks both in absolute terms and as compared to other ecosystem services is uncertain and sensitive to underlying assumptions regarding payback period and discount rate because risk of flood increases probabilistically with uncertain future sea level rise (Figure 3). For instance, over a 20-year payback period, avoided flood risks account for \$52M (90% CI: \$4.4M–\$150M) at a 7% discount rate or \$100M (90% CI: \$8.6M–\$300M) at a 3% discount rate, accounting for 80–83% of total valued ecosystem services. Therefore, ecosystem services other than flood protection may be important for offsetting or justifying upfront costs under assumptions of highly discounted future flooding risks or shorter decision-making horizons.

3.2. Water quality

The valued water quality benefits of the marsh restoration scenarios are very likely to be smaller than the flood protection benefits, and uncertainty in the magnitude of benefits is constant over time. Over a 50-year payback period, net benefits of restoration range from \$4.9M (7% discount rate; 90% CI: –\$6.1M to \$15.8M) to \$9.0M (3% discount rate; 90% CI: \$–11.3M to \$29.1M) from water quality improvements. Negative values correspond to low-probability (~20%) outcomes where a restored marsh is a net source rather than sink of P and where this more than offsets gains from N removal (Section 2.5).

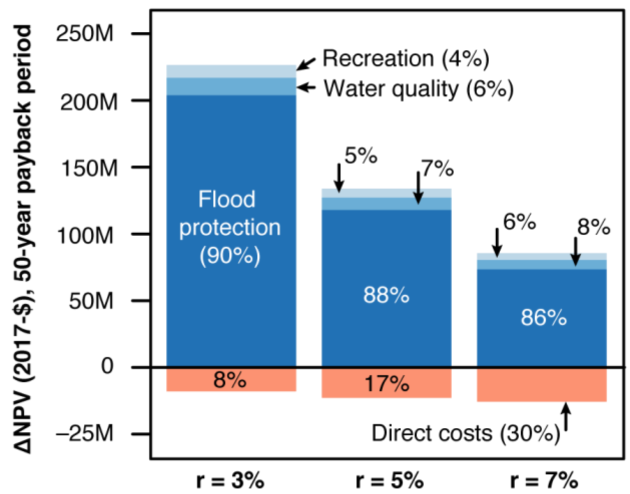

Figure 6: Difference of net present value (ΔNPV) for marsh restoration Scenario ‘C’ vs. no-action Scenario ‘A’ for a 50-year payback period for three discount rates (*r*). Percentages reported are fractions of gross benefits. Direct costs represent net additional expenditures for rehabilitation. Carbon sequestration is < 1% for all discount rates and is omitted for clarity. Values correspond to 50th percentile simulation.

Although water quality benefits are in general relatively low compared to flood protection benefits, this may still be a high estimate. We calculate P and N removal efficiencies as a function of hydraulic loading rate which is based on the mean annual discharge through Gallinas Creek and the total surface area of McInnis Marsh, whereas in reality a fraction of the flow through the Creek will bypass the Marsh even under restoration scenarios.

Over shorter payback horizons where annual flood risks are relatively low, other ecosystem services including water quality benefits account for a greater share of the total and may justify or partially offset upfront investments. For instance, in the first year after restoration, water quality benefits account for 27% of total annual benefits of restoration (mean value of roughly \$337,000 for any discount rate).

3.3. Recreation

Similar to benefits from improved water quality, expected benefits from recreation are smaller than expected benefits from flood protection, and we consider that the uncertainty in the magnitude of these benefits is constant with time. Over a 50-year payback period, net benefits of restoration range from \$5.0M (7% discount rate; 90% CI: \$1.0M–\$9.4M) to \$9.5M (3% discount rate; 90% CI: \$2.0M–\$17.6M) for recreational uses. This accounts for 4–6% of total ecosystem service benefits. Conversely, in the first year after restoration, recreational value accounts for 26% of total annual benefits of restoration (mean value of roughly \$320,000 for any discount rate).

3.4. Carbon sequestration

The net economic value of carbon sequestration is small due to the relatively small marshland areas that will be created under either restoration scenario relative to present-day areas (Table 4). At present day and under no-action Scenario ‘A’, the 50-year NPV ranges from \$41,810 (90% CI: \$34,600–\$50,890 7% discount rate) to \$173,100 (90% CI: \$143,200–\$210,600; 3% discount rate). Restoration Scenario ‘C’ increases this ecosystem benefit by \$28,250 (90% CI: \$19,620–\$35,710; 3% discount rate) or \$6,823 (90% CI: \$4,739–\$8,626; 7% discount rate). For all payback periods, the marginal increase in carbon sequestration accounts for < 1% of total ecosystem services provided.

3.5. Sediment management

Long-term sediment management costs associated with no-action Scenario ‘A’ (\$1.05M ± \$0.3M per year) add up to between \$15M (90% CI: \$8.1M–\$21.9M; 7% discount rate) to \$27.6M (90% CI: \$14.9M–\$40.3M, 3% discount rate) over 50 years. Up-front earthworks and recurring dredging for rehabilitation Scenario ‘B’ add up to between \$35.17 (90% CI: \$25.1M–\$44.0M; 7% discount rate) and \$45.75M (90% CI: \$31.25M–\$58.3M; 3% discount rate) over 50 years. At low discount rates, costs for Scenario ‘C’ are roughly the same as Scenario ‘B’ (e.g., mean NPV

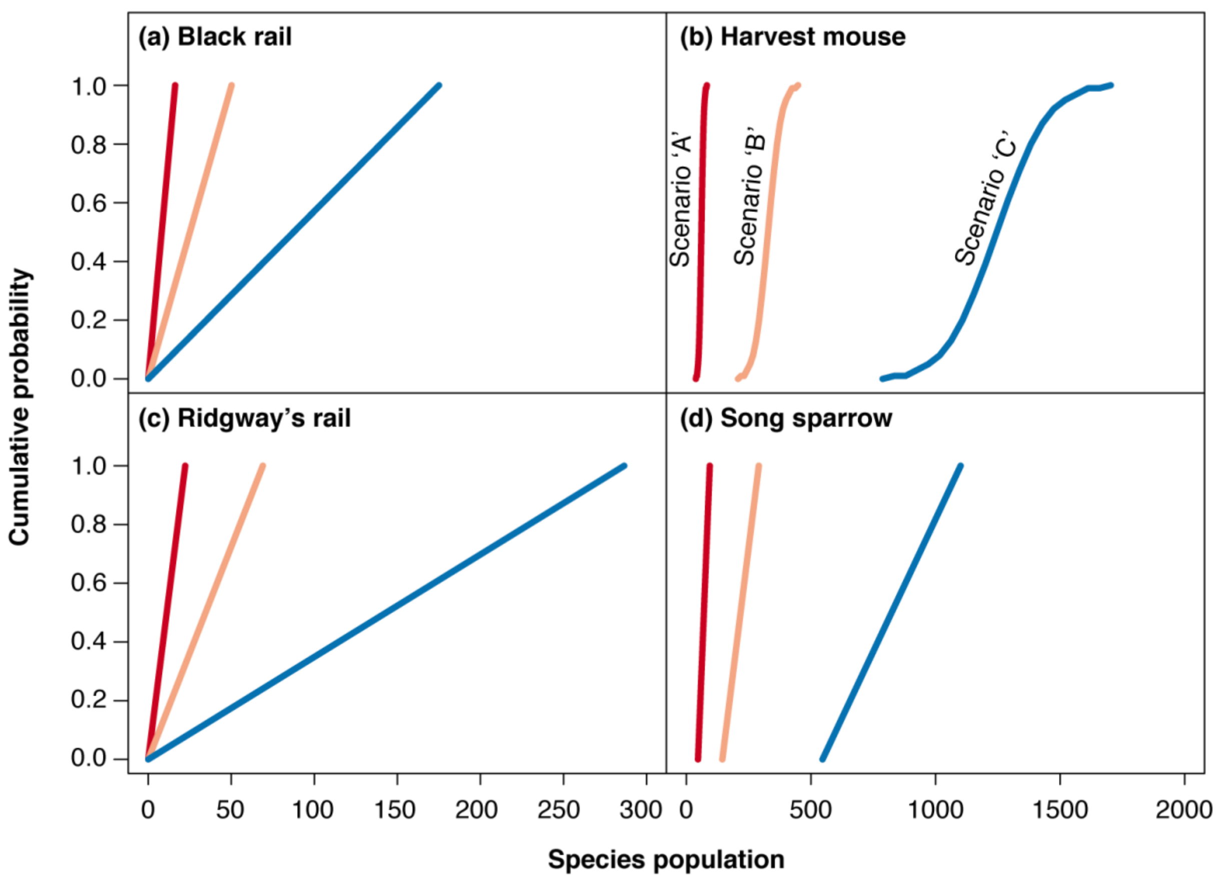

Figure 7: Cumulative probabilities of four key species considered under no-action Scenario ‘A’ and restoration Scenarios ‘B’ and ‘C’.

of $45.5 for Scenario ‘C’ vs. $45.8M for Scenario ‘B’, 3% discount rate, 50-year payback period). When future costs are more heavily discounted, higher up-front costs for Scenario ‘C’ result in a 50-year payback period roughly 10% higher for Scenario ‘C’ than for Scenario ‘B’ (i.e., mean NPV of $40.7M at 7% discount rate). The costs of no action are smaller than the costs of rehabilitation Scenarios ‘B’ and ‘C’ under all discount rates and payback periods considered. (However, as discussed earlier, the additional costs of rehabilitation are almost certainly recovered through enhanced ecosystem service provision.)

3.6. Species abundance

This analysis considered the possible impacts of wetland restoration on population density and abundance of black rail, Ridgway’s rail, song sparrow and harvest mouse as a function of habitat area created (Section 2.9). These species are important indicators of overall habitat health and biodiversity. For instance, harvest mice serve as prey for local bird populations (Konishi 2003). However, no economic value for these species has been identified, and so we do not include these in the valuation of overall benefits of restoration in Scenarios ‘B’ or ‘C’.

The effect of restoration interventions on species abundance is uncertain, and the range of possible outcomes is sensitive to whether wetland restoration is expected to increase species density (individuals per unit area) or just increase habitat area (area available as habitat) as well as to the initial uncertainty in baseline population estimates (Figure 7). Scenario ‘C’ contemplates the restoration of tidal connectivity which is expected to be associated with an increase in density of 5–25% of bird species (Spautz et al. 2006) and an increase in habitat area for bird and mammal species beyond that in Scenario ‘B’ (Kamman Hydrology & Engineering 2016)

4. Discussion

This analysis shows how conceptual models of human interventions in coastal marshes, intermediate biophysical processes and resulting ecosystem services can be parameterized to compare potential interventions and inform decision-making. We demonstrate that a probabilistic framework can reflect the substantial uncertainties inherent in environmental systems and still produce prospective site-specific estimates of economic value narrower than the overall variability across systems. For example, we estimate a mean (90% CI) annual value of restoration of approximately 56,110 (5,616–160,411) $ ha^{-1} year^{-1} (50-year period, 3% discount rate, Scenario ‘C’ vs. Scenario ‘A’) compared to overall mean values ranging between < 2 $ ha^{-1} yr^{-1} to > 340,000 $ ha^{-1} yr^{-1} (2017-$) across sites, not including within-site uncertainties (Brander et al. 2006).

Under most assumptions for discount rate, return period and confidence level, flood protection benefits dominate overall ecosystem service value. However, other benefits (notably recreation and water quality) are important for offsetting costs under short payback periods or where future benefits are heavily discounted, because most benefits related to flood risk abatement accrued to later years. For example, expected yearly probability of flood in the no-intervention scenario exceeds 10% only after approximately 20 years (Figure 3). Figure 8 illustrates how non-flood-related ecosystem services account for more than half of overall ecosystem services for payback periods of up to four years. As payback period increases, the importance of the flood-protection benefit increases to between 86–90% of the total, depending on the discount rate considered. The composition of the non-flood-related ecosystem services is illustrated in Figure 6 above.

Carbon sequestration is in general estimated to be a very small part of the overall ecosystem service value of restoration in the case of McInnis Marsh. This is because the site is already serving this function, restoration may increase this only marginally, and because the site is relatively small. However, carbon sequestration may be an important benefit on the scale of regional wetland restoration or development projects, especially where net sources are converted to net sinks (Chmura et al. 2003).

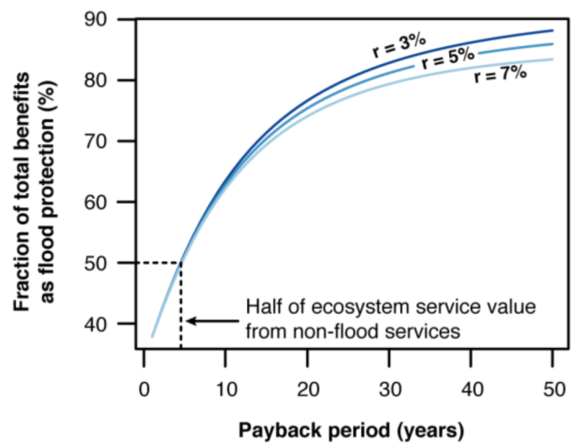

Figure 8: Fraction of overall benefits of restoration accounted for by avoided flooding as a function of payback period and discount rate for 50th percentile simulation.

This analysis considers somewhat simplified versions of actual management options under consideration and uses idealized and simplified statistical representations of the effects of site restoration on regional hydrology subject to wide uncertainties. In particular, we consider uncorrelated uncertainties between a binary risk of flood event and a continuously distributed magnitude of damages, whereas in reality, flood intensity is positively associated with magnitude of damage and negatively associated with frequency (Dutta et al. 2003). Uncertainties in this analysis could therefore be narrowed by integrating more detailed site-specific hydrologic modeling, which is beyond the scope of this analysis. It is also possible that more site-specific economic valuation data may emerge, which may change the magnitude of benefits considered here. In particular, we have not identified a preexisting, geographically relevant economic valuation for abundance of the species we studied, and species abundance is therefore excluded from our economic valuation. Therefore, the total benefits of restoration may be understated. Elicitation of stakeholder valuation of species abundance and/or more detailed ecological modeling describing the role of these species within the overall local ecosystem and their impact on economically valuable activities (e.g., a possible relationship between harvest mouse populations and opportunities for recreational birding) could allow for these benefits to be more accurately characterized. Overall, the work presented here should be taken as a template for future analysis rather than a definitive statement about the relative merits of site-specific interventions.

This template may be of particular use in comparing benefits and costs of other opportunities for coastal restoration or management across the San Francisco Bay area, which are likely to share many of the same ecosystem services described here. For instance, at least 40,000 acres of tidal wetland around San Francisco Bay have been identified as targets for restoration since 2008, but only approximately one third of this area has been restored to date (Coastal Conservancy 2018; South Bay Salt Pond Restoration Project 2008; 2015). More broadly, the predictive, probabilistic and multi-attribute nature of this analysis provides a template for analysis of ecosystem services in other contexts and may be adapted to cover services and hazards not relevant to the case study developed here. For instance, marshes play an important role in the lifecycle of mosquitoes, which in tropical regions pose significant public health risks (Walton and Workman 1998). Meanwhile, attenuation of storm surges is a principal benefit of marshlands that abut the ocean (Stark et al. 2015).

There has been rapidly increasing interest in the development of modeling capacity linking biophysical and social systems to each other and to quantifiable endpoints of interest to economists and policy-makers (Boyd et al. 2015; Liu et al. 2007). However, emerging models are increasingly computationally and conceptually complex and often feature inadequate coupling across interconnected systems, limiting support for overall uncertainty quantification (Ascough et al. 2008; Little et al. 2019; Rosa and Dietz 1998). We have demonstrated that the decision-interpretability of environmental models is contingent on quantitative characterizations of uncertainties, nonstationarities and decision-making preferences. Here, risk tolerance, payback period and discount rate have all had large impacts on the magnitude and distribution among stakeholders of the costs and benefits of environmental management scenarios. We therefore use coastal wetland rehabilitation as a case study to argue more broadly for decision support models that are fundamentally probabilistic and that are developed with equal support for biophysical as well as for economic analysis. The analysis presented here points to the importance of continued development of methods such as biophysical model emulation that allow for models of complex physical processes to be nested within decision-analytic frameworks.

5. Acknowledgments

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