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# San Francisco Bay Sea-Level Rise Website

# A PRBO online decision support tool for managers, planners, conservation practitioners and scientists Technical Report

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Phase II Report to the California State Coastal Conservancy Version 1.0 March, 2012

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#### Suggested citation:

Veloz, S., N. Nur, L. Salas, D. Stralberg, D. Jongsomjit, J. Wood, L. Liu, & G. Ballard. 2012. San Francisco Bay Sea-Level Rise Website. A PRBO online decision support tool for managers, planners, conservation practitioners and scientists. Phase II report to the California State Coastal Conservancy. <u>http://data.prbo.org/apps/sfbslr/PRBOCoastalConservancyTechnicalReport\_Mar2012.pdf</u>. Accessed <date accessed>

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# **EXECUTIVE SUMMARY**

We developed scenarios of climate change impacts on tidal marsh vegetation and bird species from 2010-2110 based on low or high rates of sea-level rise (0.52 or 1.65 m in 100 yr) and low or high suspended sediment availability. We:

(1) assessed potential climate change effects on San Francisco Estuary (Suisun, San Pablo and San Francisco Bays) tidal marsh habitats and bird populations representing a range of federal and state special status listings: Clapper Rail, Black Rail, Common Yellowthroat, Marsh Wren, and Song Sparrow;

(2) identified priority sites for tidal marsh conservation and restoration;

(3) developed a readily updatable web-based mapping tool for managers to interactively display and query results; and,

(4) communicated conservation priorities to management agencies, conservation organizations and the public.

# **Results:**

#### **Tidal Marsh:**

- Under high future sediment availability, tidal marsh habitat is expected to persist and extend to regions with high suspended sediment concentrations, such as in northern Marin County, along the Petaluma River and in southern San Francisco Bay, even under high sea-level rise (SLR) scenarios.
- However, with sediment concentrations of 200 mg/L or less, tidal marshes will only be sustainable over 100 years at locations with elevations currently at or above 0.3 m above mean higher high water with a high sea-level rise scenario.
- For high SLR and low sediment availability scenarios, existing high-marsh and midmarsh habitat are predicted to be mostly replaced by low-marsh, mudflats and subtidal areas by 2110.
- Tidal marsh restoration efforts will be most successful if implemented during the first half of the 21st century so that marsh elevations are high enough to maintain sustainable accretion rates in the face of increasing rates of sea-level rise projected for the second half of the 21st century.
- Very little currently undeveloped, un-diked area exists that is predicted to support the migration of future tidal marsh habitat into upland areas (up to 3,300 ha by 2100).
- However, an additional 2,000-7,000 ha could support tidal marsh migration into currently upland habitat by removing barriers to tidal action.
- Removal of barriers to tidal action could support additional marsh habitat (up to 32,500 ha under a low SLR/high sediment scenario by 2110).

**Plants:** 

 Models of plant species distributions were all heavily influenced by summer salinity and tidal range, but species exhibited individualistic responses to future scenarios depending on their tolerances to physical variables. The probabilities of occurrence of species such as cattail (*Typha spp.*), *Schoenoplectus acutus*, and perennial pepperweed (*Lepidium latifolium*) are all predicted to decline from current levels by 2110 under most future scenarios across the entire estuary. At the same time, the probability of occurrence of other species, such as *Sarcocornia pacifica* is predicted to increase from current levels by 2110 under high sea-level rise scenarios.

#### **Birds:**

- We summarized bird population projections given the projected habitat quality of areas currently open to tidal action (areas where tidal flow is not restricted by levees).
- Our long term monitoring data provided an improved ability to account for varying detection probabilities among bird species and to incorporate the temporal variation in site occupancy and abundance.
- The Estuary-wide populations of Black Rails and Song Sparrows are closely tied to the availability of mid and high tidal marsh habitat and future projections could increase or decrease from current level depending upon the scenario.
- The Estuary-wide population of Common Yellowthroats and Marsh Wrens are projected to decline for most scenarios, with declines most severe in the high sealevel rise scenarios.
- For all bird species studied, uncertainty in future population numbers increases in the second half of the 21st century, due primarily to the differences between the two sea-level rise scenarios we tested.
- Bird population declines are generally predicted to be less severe in the high sediment scenarios compared to low sediment; thus maintaining adequate sediment in tidal marsh systems could benefit bird populations.

#### **Restoration Prioritization**

- We ranked the Estuary's wetland landscape based on the importance of habitat to each of the five tidal marsh bird species (based on current and projected future habitat) to prioritize conservation and restoration efforts and to evaluate potential land use changes that could eliminate or limit potential tidal marsh habitat in the future.
- We found substantial differences in the tidal marsh prioritization when using only current tidal marsh bird predictions compared to using both current predictions and projections based on future scenarios suggesting that climate change will alter the locations of important tidal marsh bird habitat.
- Additionally we used the conservation planning software Zonation to rank 72 existing or proposed restoration projects based on the difference in ranking in restoration areas when the project was included or excluded from the conservation network (see Summary table below).
- We found that all restoration projects contribute some habitat that was of greater value to the conservation network but some projects contributed a greater amount of habitat or contributed habitat that was of higher quality for tidal marsh birds.

#### **Caveats**

- Our results are sensitive to the availability of suspended sediment and our estimates of the spatial distribution of sediment in the estuary do not incorporate fine scale heterogeneity in sediment availability.
- The marsh accretion model is a one dimensional model and therefore does not account for the transport of sediment or other processes such as erosion. However, there is currently no other alternative modeling framework available for projecting these processes at the spatial and temporal scales applied in this report.
- The restoration prioritization analyses only evaluated the potential habitat available for tidal marsh birds. Including other taxa would likely change the results. We recommend that future efforts should include the habitat needs of other taxa such as shore birds.
- We only evaluated restoration projects for which we had GIS polygons available and that overlapped areas where we had model results. Omission of restoration projects from our evaluation only means that we were unable to evaluate the project and says nothing about the potential benefits of these projects for tidal marsh birds.
- We did not include details of individual projects in our evaluation. For example, we did not change our base elevation layer to incorporate plans to raise initial elevations in subsided locations. Project specific plans could be incorporated in future analyses if the information is available and is spatially explicit.

#### **On-line Decision Support Tool**

- We made our findings available as an on-line decision support tool with interactive maps, the SF Bay SLR Tool (www.prbo.org/sfbayslr). The tool can be used, for example, by conservation planners at fine spatial scales to identify current upland areas that are projected to be future tidal marsh that could support tidal marsh plants and birds.
- Users can explore the range of responses of locations/regions or species across our scenarios to assess how sensitive specific locations are to the uncertainty in future conditions.
- The tool can also identify future restoration sites which are projected to be resilient to climate change but are currently behind levees or other barriers to tidal influence.

#### Outreach

 We continue to engage federal, state, regional and local decision makers to facilitate use of this on-line tool and to advance the development of adaptation strategies addressing sea-level rise impacts on tidal marshes as well as the use of tidal marshes to help mitigate negative impacts on human infrastructure. **Currently Proposed and Existing Wetland Restoration Projects – Importance to Tidal Marsh Birds.** Rankings of the contribution to an optimal conservation network of currently proposed or existing wetland restoration projects within the San Francisco Estuary. This analysis only includes the importance of habitat to tidal marsh birds. A low rank does not mean that a project is not valuable but rather that the biological value of restored tidal marsh bird habitat was less than what we project that other restoration projects could provide per acre. We were unable to evaluate all restoration projects in the estuary due to data availability and the omission of a project is not an indication of the value of the project for enhancing the habitat for tidal marsh birds.

Restoration Project	Rank	Restoration Project	Ranl
Bair Island	1	Oro Loma Marsh	37
Napa River Salt Pond- Camp Two	2	South Bay Salt Pond AB1	38
San Mateo Baylands	3	Napa River Salt Pond 6	39
Napa River Salt Pond 8	4	Eden Landing Pond E8A	40
Lake Merritt	5	South Bay Salt Pond AB2	41
Candelstick - Yosemite Slough	6	Napa River Salt Pond 2	42
Cullinan Ranch	7	South Bay Salt Pond E4	43
Stanley Ranch	8	North Parcel - Leonard Ranch	44
Skaggs Island	9	Napa River Salt Pond 1	45
South Bay Salt Pond SF2	10	Sears Point Restoration	46
Wingo East	11	South Bay Salt Pond E5	47
South Bay Salt Pond A8S	12	South Bay Salt Pond E6C	48
River Park	13	Napa River Salt Pond 1A	49
South Bay Salt Pond R5	14	Albany Marsh Expansion	50
South Bay Salt Pond E2	15	South Bay Salt Pond E5C	51
Ringstrom Bay	16	Simmon's Slough	52
South Bay Salt Pond S5	17	South Bay Salt Pond A2W	53
South Bay Salt Pond R4	18	Scottsdale Marsh	54
Napa River Salt Pond 6A	19	Novato Creek	55
Eden Landing Ecological Reserve	20	South Bay Salt Pond A23	56
South Bay Salt Pond E8	21	South Bay Salt Pond A22	57
Napa River Salt Pond 7A	22	Knapp Tract	58
South Bay Salt Pond E6B	23	Eden Landing Ponds E15	59
South Bay Salt Pond E1	24	South Bay Salt Pond A3N	60
Napa River Flood Control Project	25	South Bay Salt Pond E12	61
South Bay Salt Pond E6A	26	South Bay Salt Pond A5	62
Berkeley Meadow - Eastshore State Park	27	South Bay Salt Pond E14	63
Eden Landing Ponds E9	28	South Bay Salt Pond A16	64
South Bay Salt Pond R2	29	South Bay Salt Pond E1C	65
South Bay Salt Pond E7	30	South Bay Salt Pond A7	66
Bahia	31	South Bay Salt Pond A17	67
Napa River Salt Pond 7	32	South Bay Salt Pond A14	68
Ravenswood Preserve	33	South Bay Salt Pond A15	69
South Bay Salt Pond R3	34	Western Stege Marsh	70
South Bay Salt Pond A1	35	South Bay Salt Pond A13	71
Oliver Property	36	South Bay Salt Pond A11	72

# **INTRODUCTION**

Tidal marsh habitat plays a critical ecological function in estuarine ecosystems on a global, national, and regional scale (Greenberg et al. 2006). It supports an array of plant and animal species, many of them Threatened, Endangered or of Special Concern, including many endemic species or subspecies that have evolved adaptations to this saline environment (Greenberg et al. 2006). Additionally tidal marshes provide a variety of ecosystem services such as flood protection and carbon sequestration with the economic values of tidal marshes globally estimated to be worth \$10,000/ha/yr (Costanza et al. 1997). Tidal marsh habitat has been severely altered and degraded globally, while on a local level, 80% of the historic habitat in the San Francisco Estuary (Suisun, San Pablo and San Francisco Bays; Figure 1) has been lost since 1800 (Goals Project 1999, Takekawa et al. 2006). In addition to concern about historic changes and current dependency of biota, we must also understand and anticipate the impact of climate change, both changes that are already under-way and future changes, in order to best guide adaptive conservation and management of this habitat and its ecosystems. Tidal marshes occupy the zone between tidal mud flats and upland areas above the high tide line. Therefore, these marshes are highly sensitive to increases in sea level (Kirwan et al. 2010). In addition to the impacts of sea-level rise on habitat availability, loss of marsh elevation in the future can have deleterious impacts on ecological function of the marsh ecosystem. Climate change is expected to bring about changes in salinity as well, which will affect plant species distribution and abundance in the marsh habitat. Bird and other wildlife populations in turn are dependent on plant species for foraging, nesting, roosting, and as part of the food web supported by primary consumers (e.g., herbivorous invertebrates). Thus, birds and other wildlife may be impacted by changes in tidal-marsh-associated plants, reflecting changes in salinity and inundation, as well as by the direct impact of changes in salinity and other physical factors.

The project reported here is Phase II of a larger, three-phase effort to develop specific information to guide managers at the local and regional level in successfully managing wildlife populations, given current threats and future impacts of climate change. In Phase I, we carried out a collaborative study to improve understanding of how marsh habitat will change in the future within the San Francisco Estuary. The first phase examined geomorphological change with respect to a series of scenarios designed to address key uncertainties of physical processes in the future. The uncertainties addressed the wide range in current estimates of sea-level rise (0.2 m to 2 m over 100 years; IPCC 2007, Vermeer and Rahmstorf 2009) and the poor understanding of whether marsh accretion can keep pace with rising sea-levels (Craft et al. 2009, Kirwin and Guntenspergen 2009) by examining different projections for future sediment supply, and sea-level rise using a dynamic sediment accretion model. Results indicate that tidal marshes can keep pace with high rates of sea-level rise (1.65m by 2110) if there is a sufficiently high supply of suspended sediments (Stralberg et al. 2011). With intermediate to low sediment availability, marsh sustainability is highly dependent on the rate of sea-level rise (Stralberg et al. 2011.). An increase in the overall area of marsh habitat was projected for the low SLR (0.5 m / century) scenarios. Projections of mid and high marsh loss for the high SLR scenarios ranged from -16% to -93%.

The next two phases of the project consider the direct and indirect impacts of climate change on plants and birds in the tidal marsh habitat of the San Francisco Estuary. In Phase II, reported here, we modeled the anticipated future distribution of key tidal marsh plant species and the distribution and abundance of focal tidal marsh bird populations, as well as conservation priorities for specific tidal marshes in the context of our findings. This builds directly on the geomorphic modeling framework and results described above (Stralberg et al. 2011), and considers the same range of scenarios regarding sea-level rise, sediment supply. Phase III, currently under way, is to consider demographic impacts of climate change, such as impacts of inundation on annual reproductive success or over-winter survival, and builds on the current modeling results regarding distribution and abundance. In the future, we hope to expand our analyses to other species, including shorebirds. We also would like to incorporate the results of dynamic sediment transport models to more realistically model the interaction between mudflats and tidal marshes.

In Phase II, we focused on five tidal marsh bird species: Clapper Rail, Black Rail, Common Yellowthroat, Marsh Wren, and Song Sparrow. Each species is a year-round resident and is dependent on, or strongly associated with, tidal marsh habitat (Goals Project 2000). All but the Marsh Wren are species of high conservation concern. Two species are rails; the California Clapper Rail subspecies (Rallus longirostris obsoletus) is a Federally Endangered species and a focus of the USFWS Draft Recovery Plan for Tidal Marsh Ecosystems of Northern and Central California (2009) while the California Black Rail subspecies (Laterallus jamaicensis coturniculus), is a California Threatened species. The other three species are tidal marsh-associated songbirds, two of which are California bird species of special concern (Shuford and Gardali 2008). The Song Sparrow has three subspecies that are endemic to the San Francisco Estuary tidal marshes (Melospiza melodia pusillula, M. m. samuelis, and M. m. maxillaris; Marshall and Dedrick 1994), while the Common Yellowthroat has one subspecies endemic to the Estuary, the "Salt marsh Common Yellowthroat" (Geothlypis trichas sinuosa). Thus, these species are critical to consider when evaluating the impact of several multi-million dollar restoration projects which are currently planned or ongoing. We also chose these five focal species because of extensive Estuary-wide population studies, dating from 1996 (or earlier in the case of the two rail species) to the present, conducted by PRBO and partners. Detailed information regarding distribution and abundance of these species is available for the last 5 to 15 years.

#### **Specific Goals**

Our overall goal with this project is to help ensure the conservation of San Francisco Estuary tidal marsh habitats and the birds and other wildlife dependent upon them by evaluating the threat posed by sea-level rise, changing salinity, and other climate change related-conditions. Phase II of our project (reported here) was designed to (1) assess the potential effects of climate change on tidal marsh habitats and bird populations, (2) identify priority sites for tidal marsh conservation and restoration, (3) develop a readily updatable web-based mapping tool for managers to interactively display and query results, and (4) communicate conservation priorities to management agencies, conservation organizations and the public. This report deals explicitly with goals 1 and 2 above. Goal 3 has been completed and the results from Phase I and

II are available online (<u>www.prbo.org/sfbayslr</u>). Goal 4 is ongoing and includes demonstrations and presentations given to government agencies, non-profit organizations and scientific meetings (see list of presentations given in Appendix 1).

To achieve goals 1 and 2, we accomplished the following objectives:

- (1) Develop predictive models of focal tidal marsh plant species for current distribution Estuary-wide, and infer future distributions using an available set of physical variables that includes elevation relative to tidal inundation and salinity (Table 1, Table 3).
- (2) Develop predictive models of focal tidal marsh bird species' current distribution and abundance Estuary-wide, and infer future distributions, using an available set of physical variables, comparable to that used for plant modeling.
- (3) Using the maps of predicted tidal marsh species abundance, rank the landscape in terms of conservation priority given current and future tidal marsh ecosystem conditions. These maps can be used to evaluate where tidal marsh habitat is resilient to future sealevel rise and remains as high quality habitat for tidal marsh species. They also can be used to prioritize proposed restoration projects with regards to their resiliency to the effects of sea level rise.

**Table 1.** Combinations of future scenarios used for projecting the distributions of tidal marsh habitat, vegetation and tidal marsh birds. The values for the high and low sediment concentrations varied by study sub-regions. The low and high sea-level rise scenarios predict 0.52 m and 1.65 m of sea-level rise from 2010 to 2110, respectively. For locations and extent of sub-regions, see figure 1. The values for each sub-region were based on field data and expert opinion where data was unavailable (Stralberg et al. 2011).

	Sediment Concentration		
	(mg/	L)	
Sub-region Name	Low	High	
South Bay	150	300	
Redwood City	50	150	
Hayward	50	150	
San Francisco	25	100	
Oakland	50	100	
South Marin	25	50	
East Bay	50	100	
North Marin	100	300	
Pinole	50	150	
Petaluma River	150	300	
San Pablo North Shore	150	300	
Napa River	100	150	
South Suisun	150	300	
SE Suisun	25	100	
Suisun Marsh	25	100	

# **METHODS**

## **Study area**

Our modeling efforts included the entire area of suitable current or future elevation for tidal marsh habitat in San Francisco Estuary, including Suisun, San Pablo, and San Francisco Bays (Figure 1). We used the USGS national elevation dataset (NED) to delineate upland boundaries for our modeling. The upper limit was defined as the 15.2 m (50-ft.) elevation contour line plus a 100-m horizontal buffer to account for error in the NED, resulting in a total study area of just over 186,000 ha. Bird and vegetation modeling was restricted exclusively to tidal marsh habitat as we did not have survey data incorporating vegetation or bird distributions in mudflats or upland areas. Vegetation and bird survey sites were located in tidal marshes throughout the region, extending as far upstream as Brown's Island at the western edge of the Sacramento/San Joaquin Delta (Figure 1). Sites, and survey locations within sites, were selected to sample the range of environmental conditions which occur throughout the Estuary in this habitat type.

# **Biological parameters**

#### Survey methods

Vegetation was sampled at point count station locations (see below), with mature marshes sampled once every three to four years and younger marshes sampled more frequently (Spautz et al., 2006). Fifteen plant species were selected for initial modeling based on their prevalence in our surveys and their hypothesized importance in tidal marsh systems. Species modeled were: *Distichlis spicata* (salt grass), *Frankenia salina* (alkali heath), *Grindelia stricta* (gumplant), *Jaumea carnosa* (jaumea), *Juncus* spp. (rushes), *Lepidium latifolium* (perennial pepperweed), *Phragmites australis* (common reed), *Sarcocornia pacifica* (pickleweed), *Schoenoplectus acutus* (tule), *Schoenoplectus americanus* (three-square bulrush), *Schoenoplectus californicus* (California bulrush/tule), *Bolboschoenus maritimus* (alkali bulrush), *Spartina foliosa* (Pacific cordgrass), *"Spartina"* which specifically refers to the hybrid between non-native *Spartina alterniflora* (smooth cordgrass) and other *Spartina* species, and *Typha* spp. (cattail). Presence/absence was scored as 1 if percent cover was greater than zero, and zero otherwise. Predictive models were developed for all fifteen species. We then chose eight species for presenting detailed results, based on a combination of predictive performance of the statistical model and our assessment of ecological importance.

Surveys for Clapper Rails required a specialized survey method (Liu *et al.* 2009); these data were available from 2005 to 2010. All six years of survey data were used in the bird modeling for this species to provide a long-term average for "current" distribution. Clapper Rail surveys were conducted at multiple survey sites in each marsh (1 to 21 survey points per site; median =5 survey points). Each survey point location was visited multiple times during the breeding season, from mid-January to mid-April. See Liu et al (2009) for more details on protocol and data handling.

**Figure 1** San Francisco Estuary tidal marsh regions (Suisun, San Pablo, and San Francisco Bays) and avian survey sites used in the analysis for Clapper Rail and for the other four tidal marsh bird species. Each Clapper Rail survey site contained 1 to 21 individual point count locations (median = 5 points); each tidal marsh bird survey transect contained 1 to 17 individual point count locations (median = 8 points). Polygons indicate study sub-regions which individually prescribed suspended-sediment concentrations (Table 1).



Methods used for Common Yellowthroats, Marsh Wrens and Song Sparrows are described in Spautz et al. (2006) and Stralberg et al. (2010). More detailed information on surveys for these species and the survey methods for Black Rails are available in Liu et al. (2007). For these species, we used the most recent 10 years of survey data, i.e., 2000 to 2009, to provide a long-term average for "current" distribution. Detections were from the breeding season (mid-March to end of May), excluded juveniles, and were within 50 m radius of the point count-center (Spautz et al. 2006). Most points were visited twice per year, rarely three or four times.

#### Analysis of bird survey observations

An important aspect of the Clapper Rail survey data is the large number of zeroes in the dataset, due to absence of the species at a site or low probability of detection during a survey (see "Estimating Absolute Abundance" section below). The Clapper Rail is absent from many sites around the Bay for reasons not captured by the set of covariates in our models. For model fitting, therefore, we only used sites with detections in any survey point and any survey year, thus ensuring that only sites where the rails are known to occur were included in the sample. Thus we did not make predictions for Suisun Bay (i.e., there were no surveys in this area that met the criteria). Filtered this way, the dataset still included points where the species was never detected, and numerous visits to points where no bird was recorded. The filtered dataset (Table 2) included 5,603 records of visits to points that were collapsed into 1,811 point-year records by taking the maximum number of detections at a point each year. That is, the number of pointyear records is the sum across all years of all points included in the sample. If tape playback was used in any visit to a point within a year, the record for the point that year was attributed to indicate tape use. We considered the maximum number detected to be a better measure of true abundance than the mean number, due to the difficulty in detecting this secretive species (Liu et al. 2009).

For the other four tidal marsh bird species, survey data spanned years 2000 to 2009. The prevalence and probability of detection of these species was adequate for including all records from all sites surveyed, regardless of the history of detections of the species at the site (except black rail, see below). The summaries of numbers of records and detections, number of points and sites surveyed for each species are shown in Table 2. As with Clapper Rail, we used the maximum number of detections per point per year to model the abundance of each species.

Black Rails have not been found during our surveys within the San Francisco Bay (but they were present in San Pablo and Suisun Bays); they have widely been reported absent as breeders in San Francisco Bay (e.g., Evens and Nur 2002). Therefore we developed models without including the surveys for the latter region and our models are summarized accordingly. However, we include extrapolations in our maps to illustrate potentially suitable habitat for the species. We note though, that projections in the San Francisco Bay for this species should only be interpreted as reflecting habitat suitability and not as the probability of occurrence. **Table 2**. Sampling effort, summary of: point-year records, point-year detections and point-yearabsences; detection probability, and ratio of maximum count to mean count for bird species included inmodels.

	#point-year records #sites (sum of point-year Detection			Max count/Mean
Species	(#points)	detections/#zeroes)	probability	count
Black Rail	36 (455)	1,424(366/1,150)	0.06	NA
Clapper Rail	85 (536)	1,811 (1,260/1,183)	0.10	NA
Marsh Wren	51 (560)	2,238 (3,397/1,140)	0.31	0.76
Common Yellowthroat	41 (447)	2,238(1,131/1,579)	0.30	0.66
Song Sparrow	66 (627)	2,238(9,705/95)	0.29	0.79

# **Physical Parameters**

Physical variables were initially selected for inclusion in the models based on previous work modeling tidal marsh habitat characteristics (Stralberg et al, 2011) and other published studies (Spautz et al, 2006, Stralberg et al. 2009, Watson and Byrne, 2009, Table3). We were limited to variables for which data were available throughout the Estuary and which would also be available for modeling future scenarios. Distance values were calculated using Euclidean distance in ArcGIS 9.3.1 (ESRI 2009) and based on layers found in San Francisco Bay Area EcoAtlas (San Francisco Estuary Institute 1998

#### **Elevation**

Initial elevation and layers derived from elevation were primarily based on Light Detection and Ranging (LiDAR) remote sensing data contributed by USGS (Knowles, 2010, Stralberg et al., 2011). The LiDAR data had a 5 m spatial resolution with a  $\pm 2 - 3$  cm vertical accuracy. The NAVD88 vertical datum of the LiDAR data was converted to a Mean Higher High Water (MHHW) reference level using NOAA tidal gauge and benchmark data. Derived elevation layers such as slope and standard deviation of elevation were all calculated in ArcGIS 9.3.1 (ESRI, 2009). Future marsh elevation layers were based on models of tidal marsh accretion (see above, Phase I; Stralberg et al. 2011) and for each future scenario new derived elevation layers, including mean slope in a 50 m radius circle, proportion of high, mid and low marsh habitat and marsh elevation standard deviation, were calculated. "Marsh elevation relative to MHHW" for these analyses was characterized in two ways: as the majority or mean of values for all pixels within the 50 m radius of the center point of each 50 m x 50 m grid cell). Mean percent rise (slope) was calculated in ArcGIS 9.3.1 based on the elevation layer for a given scenario.

#### **Sea-Level Rise Scenarios**

We chose two nonlinear sea-level rise scenarios based on guidance provided by the US Army Corps of Engineers (ACOE, 2009), which recommends scenarios modifying curves proposed by the National Research Council to extrapolate intermediate and high sea-level rise scenarios ("NRC-I" and "NRC-III", respectively). These scenarios project 0.52 m and 1.65 m of sea-level rise over the next century, with most of this change occurring within the second half of the century. These rates are similar to other recent estimates (Rahmstorf 2007, Vermeer and Rahmstorf 2009).

**Table 3.** Abbreviations used and units of measurement for physical parameters included inmodels. Also indicated (constant) is whether the parameter was allowed to vary by timeinterval in future projections.

			Constant
Variable	Abbreviation	Units	variable
		Practical Salinity Units	
Mean spring salinity	sprsalin	(PSU)	No
		Practical Salinity Units	
Mean summer salinity	sumsalin	(PSU)	No
Mean marsh elevation (relative to			
MHHW)	mhhw10mean	Meters	No
The most frequent marsh elevation in			
the cell (relative to MHHW)	mhhw10maj	Meters	No
Standard deviation of MHHW marsh			
elevation	mhhwsd	Meters	No
Tidal Range (=Difference between			
MHHW and MLLW	meanhhw	Meters	Yes
High-marsh (0.2 m to 0.3 m) proportion	mhhwhigh	Proportion	No
Mid-marsh (-0.2 m to 0.1m) proportion	mhhwmid	Proportion	No
Low-marsh (-0.5 m to -0.3 m)			
proportion	mhhwlow	Proportion	No
Mean slope	slope	Percent Rise	No
Percent of area that is channels	channelpercent	Percent	Yes
Distance to edge of bay	distbay	Meters	Yes
Distance to nearest channel	distchan	Meters	Yes
Distance to nearest levee	distlevee	Meters	Yes
Distance to nearest urban area	urbdist	Meters	Yes

#### Salinity

Maps of current mean summer salinity were calculated based on a spatial interpolation of salinity observations throughout the bay. Observation at point locations were spatially interpolated to a 50 m x 50 m grid using local polynomial interpolation in ArcGIS 9.3.1. 100-year (2000-2099) salinity projections for 50 bay segments and delta outflow values were obtained from the USGS (Cloern et al, 2011). These salinity simulations were run as part of the CASCaDE project<sup>1</sup>. We used daily salinity projections based on the Geophysical Fluid Dynamics Laboratory (GFDL) general circulation model for two emissions scenarios: B1 (low) and A2 (high). Because the SLR assumptions used in the salinity simulations were based on IPCC projections, they did not match our more recent estimates from the NRC. Thus we had to adjust

<sup>&</sup>lt;sup>1</sup> The CASCaDE project is a United States Geological Survey led effort funded by the CALFED science program aimed at determining how multiple drivers of environmental change would interact to change ecosystems targeted for restoration, http://cascade.wr.usgs.gov/index.shtm.

the salinity projections to match the NRC projections (NRC-I and NRC-III). To accomplish this, separate regression models were developed for each bay segment and for each emission scenario (B1 and A2), in order to separate the effects of SLR and delta outflows (a function of precipitation) on daily salinity values. Linear regression models were specified as Salinity = (beta 1)\* SLR x (beta 2)\*Season + (beta 3)\*net delta outflow. Seasons were defined as consecutive three month periods, with spring defined as March, April, and May and summer defined as June, July and August. Regression models were then used to predict daily salinity for the NRC-I and NRC-III SLR trajectories. The lower-end (NRC-I) SLR projections were based on models developed from lower emission (B1) salinity projections; high-end (NRC-III) SLR projections were based on models developed from higher emission (A2) salinity projections. Daily values were averaged over seasons and 20-year time periods to match our marsh elevation projections. Differences between current and future scenarios were calculated by taking the difference between the current layers and future projections. The differences were then added to the current layer to obtain future salinity projections which retain the spatial patterns of current salinity in the Estuary.

The effect of salinity on vegetation and bird distributions was hypothesized to be most extreme during the spring and summer seasons. Therefore, only these two seasons were included in the models. For vegetation models (see below), only summer salinity was included; summer salinity was presumed to have a more direct influence on vegetation distribution, and spring and summer salinity were highly correlated (Pearson's r = 0.91). For bird distribution models, we considered both salinity variables; whichever salinity variable had more relative influence in initial exploratory models was retained for final models. Additionally, bird models included bay region and observation year modeled as "factors." Clapper Rail models included a factor for whether a tape playback was used during the survey. We did not use the predicted presence of any particular plant species in the bird models, because these presence data would originate from the plant species' predictive models and these models includes the same covariates we used in the bird models. Thus, the effect of the plant species on the bird species presence or abundance is captured by the physical covariates in the bird models.

Some variables were assumed to remain unchanged across future scenarios. We assume that the location of levees and urban areas will remain largely unchanged so the distance to levee or urban areas variables remains constant. Because we have no projections for how channels will change in the future or how tidal range will change we make the simplifying assumption that that distance to nearest channel, channel percent and tidal range will not change in the future.

# **Distribution and Abundance Models**

#### Vegetation

To arrive at a candidate list of models, we initially created generalized additive models (GAMs) (Hastie et al. 2001) with cubic spline smoothers and penalty parameters with 4 degrees of freedom, following the default parameterization of the gam package in R statistical software (R Development Core Team, 2010). We evaluated all possible combinations of predictor variables and included interactions between summer salinity and the majority elevation within 50 m radius, thus allowing the effect of salinity to vary with location within a marsh. All models were

ranked according to the Akaike Information Criterion (AIC) and all of the highest ranked models within 2 AIC units of the top model (model with lowest AIC value) were retained for further analysis (Burnham and Anderson 1998).

We made final species distribution projections based on the model averaging of a bootstrapped ensemble of all retained candidate models to avoid over-fitting to a single model (Hastie et al. 2001). Ensembles were created by running 50 boot-strap iterations of each selected model per species to further avoid over-fitting (Efron, 1983). All iterations used a hold-out (20%) of the survey data to calibrate the model, with the remaining 80% split at random into 75% "out-of-bag" and 5% "in-bag" samples in each iteration. Projections from each iteration and selected model were made for the entire San Francisco Estuary. A final ensemble prediction was made by taking the weighted average of all selected model iterations, where weights were based on deviance from cross-validation of each model in the ensemble against the hold-out set. Model projections represented the weighted average probability of occurrence across all selected models and bootstraps at each grid pixel. The same models were projected to simulated future environmental conditions for all scenarios and time periods.

#### **Birds**

Tidal marsh birds were modeled using boosted regression trees (BRT) (Elith et al. 2008) BRTs have been shown to be less prone to over-fitting than standard classification and regression trees and have better predictive performance than other statistical algorithms (Elith and Graham 2009). They also have the benefit of implicitly incorporating interactions into predictions and fit non-linear responses. We used BRTs rather than GAMs because we hypothesized that the relationships between bird occurrence and physical variables would be more complex than is the case for vegetation and, if so, BRTs are more efficient at selecting more complex models from a high dimensional space than GAMs.

BRTs require the specification of three important parameters which determine the complexity of fitted models: tree complexity (number of interactions allowed), learning rate and number of trees. Fitting the BRT model requires the appropriate choice of all three parameters to maximize its predictive ability while reducing the likelihood of over-fitting on the training dataset (Elith et al. 2008). For each species, we tested all possible combinations of models with tree complexities of 1 to 5 and learning rates of 0.01, 0.005, and 0.001. The optimal combination of parameters was selected based on the predictive deviance using a 10 fold cross-validation of the models and the final number of trees fit. More trees with smaller learning rates tend to lead to more complex models. Therefore, optimal models were those which had the lowest predictive deviance with the smallest number of trees and with the highest learning rate.

We modeled predicted presence/absence in the surveyed area using BRTs with binomial link function fit to the entire dataset. We then predicted the probability of occurrence of the species in tidally influenced areas around the San Francisco Estuary using these models. Areas that are not currently vegetated but are going to be affected by sea-level rise are included in all model years, including the present, so current predictions may be unrealistic for some areas, such as young restoration sites, that have the physical characteristics of suitable habitat but do

not yet support mature vegetation. We also created binary presence/absence maps using a threshold value such that each cell was assigned either 0 (absent) or 1 (present), depending on whether it exceeded the threshold value. For Clapper Rails we chose a low threshold value (0.1) due to the low predicted probably of occurrence throughout the Estuary. For all other species the threshold used was the species prevalence in the survey dataset (Liu et. al, 2005).

The accuracy of distribution models under current conditions was assessed by calculating the area under the receiver operating characteristic curve (AUC); AUC ranges from 0 to 1 and measures the ability of a model to discriminate presence from absence across all possible thresholds of the predicted probability of occurrence. An AUC value of 1 indicates that a model has perfect discrimination, while an AUC of 0.5 means a model discriminates presence from absence no better than random. AUC < 0.5 means that a model discriminates presence from absence worse than random. The sensitivity of each species to future scenarios was evaluated by calculating the mean probability of occurrence throughout the bay under each future scenario.

The goal of our study was to evaluate the sensitivity of species distribution to different future scenarios, not to test hypotheses about the correlations between biophysical variables and species occurrence or abundance. Even so, we were interested to know the relative influence of each variable in the final model. The algorithm we used estimates this relative influence by taking the number of times a variable was chosen for a split in a tree, weighted by the squared improvement to the model attributed to the spit and then averaged across all trees (Elith et al. 2008) so that the influence of all variables in the models sums to 100%. Additionally, we generated partial response curves for each predictor variable in presence absence models by making predictions from the binomial boosted regression tree model to each environmental variable while holding all other variables at their mean value.

The number of detections per survey per ha was used as a measure of relative abundance (Nur et al. 1999). This variable was modeled using the log transformed maximum counts at a survey point from each survey year, with a Gaussian distribution of residuals. We then used the predicted presence/absence layer as a mask, such that abundance was predicted only for cells for which presence was predicted for that cell (i.e., above the threshold value). Thus, abundance was predicted conditional on the BRT predicting that the species was present in that cell. The total abundance of the Estuary was estimated by adding the predicted abundance across all tidal marsh cells in the San Francisco Estuary, after correcting for the difference between the area surveyed at each point and the cell size (details below).

Analysis of observations of individuals detected during avian surveys can be used to predict relative abundance and presence/absence for each species. However, in order to predict true, absolute abundance we needed to estimate the probability that a species was present during a survey but was not detected (Buckland et al 1993; Thomas et al 2009, Royle et al. 2005). To do so we discriminated between true zeroes (points where the species was never detected because it was absent) and apparent zeroes (points where the species was present but was not detected). To correct for apparent zeroes (i.e., to account for probability of detection) we developed a detection correction factor. For Clapper Rails, we used the maximum counts per

three visits to a point each year to fit a simple mixture model that includes a probability of detection parameter and a single count (Poisson) parameter (Royle et al. 2005). The estimated probability of detection is with respect to three visits to a point. Detection at two visits out of three implies failure to detect the individual at one of the visits, though it was presumed present. For Marsh Wren, Song Sparrow, Black Rail and Common Yellowthroat, there were enough detections in single visits to fit a mixture model that estimated the probability of detection for a single visit for these species. In this analysis, zero detections is considered a mixture of true zeroes (species absent) and false zeroes (species present, but not detected). A single individual detected could mean that there was only one individual present or that more than one individual was present but only one was detected. We used the inverse of detection probably as our correction factor.

To estimate total absolute abundance for a species, we scaled the predicted relative abundance per surveyed area to fit the area of the prediction cell (50 m x 50 m). Since the area of a cell is 50 x 50 m, and the area surveyed by a point with limit detection radius 50 m is (50 x 50 m) x PI, the scale parameter is simply 1/PI. The scaled estimate was then corrected for the estimated probability of detection for the species (see above). Finally, for the three songbird species, we adjusted maximum detections per visit to take into account over-counting because of double counting of individuals, and counting of transients. For Song Sparrows, Common Yellowthroats, and Marsh Wrens, we determined the ratio of maximum counts per visit to mean counts per visit, and corrected the maximum count by the ratio of mean to maximum counts per visit (Table 2). Detections of the two rail species were rare, and so no adjustment was necessary.

## Landscape Prioritization

We used the conservation planning software Zonation (v.3.0; Moilanen 2007) to prioritize all current and future potential tidal marsh habitat in the San Francisco Estuary. The Zonation algorithm creates a hierarchical ranking of the landscape by iteratively removing pixels from the landscape based on their biological value to all species under consideration. Here we used the core area Zonation removal rule where at each iteration, the algorithm minimizes the loss of the species with the smallest proportion of its distribution remaining thereby retaining core areas for all species (Moilanen 2007). Maps of predicted bird densities for each time period and scenario were included as separate "species" in the analysis so that needs of each species through time and for different future scenarios are considered for evaluation (Thomson et al. 2009). We used maps of the standard deviation of the predictions for each species across the four future scenarios for each time period to discount predictions and account for uncertainty in future predictions for all Song Sparrow maps at 2050 was used to discount the predictions for Song Sparrow for each scenario at 2050. The percent of the projected abundance removed for each species during each time period ranged from approximately 5% to 45%.

To assess the effects of not considering future sea-level rise, we consider two Zonation solutions: 1. we only include the current maps of predicted abundance for each species in the Zonation analysis and 2. We include both current and future projected abundances in the Zonation solution. The difference in the two maps illustrates how prioritization of the landscape might change as we consider the habitat changes that could result from future sea-level rise.

To determine the costs of not including areas in the Zonation solution which are currently blocked from tidal action by levees we integrated two separate Zonation analyses. The first analysis treated all current and potential future tidal marsh areas as available, regardless of whether they are currently behind levees. The second analysis forced Zonation to remove areas behind levees first in the hierarchical prioritization of the landscape. The difference between the two analyses provides an indication of the replacement costs of not including areas behind levees in the optimal solution and highlights areas that could have the greatest biological benefits if restoration was implemented (Moilanen et al. 2009).

The replacement cost analysis above illustrates the value of individual pixels across the landscape. However, restoration projects are implemented at the site level where a levee might be breached to restore a given area that might contain pixels with both high and low replacement cost values. We ran two additional Zonation analyses to rank realistic restoration scenarios proposed or in progress throughout the San Francisco Estuary. For this analysis we obtained GIS polygons of existing and proposed restoration projects from the San Francisco Bay Joint Venture. We included all available polygons where there was overlap between the polygon and our model results. In some cases, the polygons for restoration projects were not included because there was no LiDAR data available at the site or the elevation at the site fell below the range which we modeled. We excluded any project that was less than one hectare or where only one hectare or less of the project overlapped with our model results. The landscape was prioritized assuming all restoration projects were implemented in the first analysis and then forcing the pixels within restoration sites to be removed first in the second analysis (assumes no restoration projects are implemented). We then used an area weighted sum to rank each project polygon for its restoration value for tidal marsh birds over the next century.

# **RESULTS**

# **Online Decision Support Tool**

Projections for all species modeled and tidal marsh habitat under current and future scenarios are available for viewing online (<u>www.prbo.org/sfbayslr</u>). The tool is meant to be used to evaluate management decisions given the range of sea-level rise and suspended sediment scenarios we tested. Because future projections of sea-level rise and sediment availability in the San Francisco Estuary are highly uncertain, we feel that a sensitivity analysis incorporating the uncertainty in future projections will enable robust decisions for planning for sea-level rise and climate change impacts. Therefore, we stress that the maps and population projections we report should not be interpreted as a precise estimate of what the future may bring. Rather, the user is encouraged to compare the responses of locations/regions or species across our scenarios to assess what the possible impacts are across all scenarios.

We have designed the tool so that it can be easily updated as new information becomes available. A new seamless two meter digital elevation model based on recently acquired LiDAR data is scheduled to be available during the summer of 2012. We plan to update our results with this data when it is available. Additionally, new projections for sea-level rise, salinity and sediment availability are also expected to become available and we intend to update our tool with this data whenever possible.

## **Physical Variables Models**

Detailed results from tidal marsh elevation modeling are provided in Stralberg et al., (2011). Here we provide brief summaries of the elevation and salinity projections to aid in the interpretation of vegetation and bird distribution modeling. We report on the changes of elevation at the scale of our vegetation and plant survey areas (50 m radius circle). In particular, we focus attention on changes in high marsh (0.2 m to 0.3 m with respect to MHHW), mid marsh (-0.2 m to 0.1m) and low marsh (-0.5 m to -0.3 m).

Our models project that tidal marsh habitat will have a dynamic response to sea-level rise in areas where tidal action is not obstructed by levees. Under low rates of sea-level rise marsh accretion allows marshes to keep pace with increasing sea levels, particularly in areas with sufficient suspended sediment concentrations. However with high rates of sea–level rise combined with low suspended sediment concentrations, large proportions of tidal marsh are converted either to mudflats or sub-tidal areas. For the low sediment high sea-level rise scenario, we project 93% of the amount of mid marsh and high marsh habitat currently present in the estuary to be lost by 2110 (Stralberg et al. 2011).

The mean amount of low marsh habitat occurring in the San Francisco Estuary is projected to increase from current levels for all scenarios except for the high sediment/low SLR rise scenario (Figure 2a). Currently low marsh habitat comprises, on average, about 10% of the 50 m radius

around our bird and vegetation survey locations (Figure 2a). For the high sea-level rise scenarios, low-marsh habitat is projected to cover on average between 40-55% of tidal marsh area in San Francisco Bay by 2090, and up to 60% of the area in San Pablo Bay for the low sediment/high sea-level rise scenario for 2090 (Figure 2a). This increase in the proportion of areas predicted to be low marsh habitat in the future goes well beyond the range of what we observe in the San Francisco Estuary today. It is likely that these low marsh areas will either erode to mudflats or continue to increase in elevation depending on the specific physical characteristics of the site. However, our one dimensional model does not incorporate these dynamics. Thus our vegetation and bird distribution models in some cases must extrapolate projections to novel conditions which may be unlikely to actually occur in the future.

Future projections for mid-marsh habitat vary greatly with respect to each of the scenarios we tested. For all scenarios, mid-marsh habitat increases by 2030 across all bay regions (Figure 2b). The increase in mid-marsh habitat is due to marsh accretion which is able to outpace the increases of sea level from either sea-level rise scenario. We project the proportion of mid marsh habitat to remain above current levels for all scenarios except the low sediment/ high sea-level rise scenario across most of the Estuary (Figure 2b). We also project the proportion of mid marsh habitat to decline under the high sediment/ high sea-level rise scenario in Suisun Bay due to the relatively low sediment values prescribed in the model within this sub-region.

**Figure 2.** Current and projected future mean low-marsh (a), mid-marsh (b), and high-marsh (c) for each 20 year period between 2010 and 2110 within San Francisco Bay (SF), San Pablo Bay (SP) and Suisun Bay (SU). Future projections are given for each combination of high/low sediment (sed) and high/low sea-level rise (SLR) scenario combinations



#### a. Mean low marsh

2090

2110

#### b. Mean mid marsh







# c. Mean high marsh







Under all scenarios, high marsh habitat is projected to decline throughout the San Francisco Estuary by 2110. Although the declines in high marsh habitat are greatest for the high sea-level rise scenarios, there is not as much variation across scenarios as in the mid and low marsh projections. However, high marsh may be under-represented under low sea-level rise and/or high sediment scenario projections. This is because the marsh accretion model we used does not take into account geomorphic processes within the marsh plain that produce heterogeneity within a marsh. Stochastic events such as extreme tides or storms may deposit material on the marsh plain creating additional high marsh habitat but the model does not simulate these events.

Currently there are approximately 7,500 hectares of potential tidal marsh habitat that are restricted from tidal action by levees (Table 4). In all scenarios, except the high sea-level rise low sediment scenario, the amount of potentially restorable habitat by removing levees increases from 2010 levels by 2110 (Table 4). With high suspended sediment concentrations, we found that the amount of potentially restorable marshes increases by over 250% by 2110 with a high sea-level rise scenario. However, under a low sediment/ high sea-level rise scenario, the amount of restorable habitat decreased by approximately 20% (Table 4). These results indicate that restoration efforts could substantially increase the availability of tidal marsh habitat by 2110 but sediment supply may need to be actively managed to ensure that restoration is resilient to high sea-level rise scenarios. Additionally we found that restoration could allow marshes to migrate into currently upland habitat further increasing the available tidal marsh habitat by 2301 ha and 6,958 ha for the high and low sea-level rise scenarios respectively by 2110 (Table 4).

**Table 4.** Area (ha) of current and potential future tidal marsh habitat and upland areas reclaimed, under different sea-level rise and sediment availability assumptions for San Francisco Bay. To demonstrate restoration potential, the potential future marsh area for currently diked lands reflects the assumption that all barriers to inundation are removed in 2010. Suspended sediment availability (SSC) high and low assumptions vary by Bay subregion. Sea-level rise (SLR) assumptions were developed by the National Research Council (low = 0.52 m/century; high = 1.65 m/century).

Year	Scenario	Current Land Status	Low Marsh	Mid Marsh	High Marsh	Total Marsh	Uplands Reclaimed
2010	Current	Diked	3,041	3,360	1,109	7,509	-
	SSC High/SLR						
2110	Low	Diked	6438	25,173	888	32,499	2,301
	SSC High/SLR						
2110	High	Diked	5759	12,971	670	19,399	6,958
2110	SSC Low/SLR Low	Diked	6240	10,485	888	17,613	2,301
	SSC Low/SLR						
2110	High	Diked	2767	2,608	670	6,045	6,958

In general, salinity is projected to increase throughout the San Francisco Estuary. However, the future salinity projections for 2030 are lower than or equal to current levels in both summer and spring (Figure 3) except for summer in San Pablo Bay (Figure 3a). Beyond 2030, salinity increases from current levels to a greater degree for the high sea-level rise scenario than for the low sea-level rise scenario.

**Figure 3.** Current (2010) and projected future mean summer (a) and spring (b) salinity for each 20 year period between 2010 and 2110 within tidal marsh areas within San Francisco Bay (SF), San Pablo Bay (SP) and Suisun Bay (SU). Future projections are given for high and low sea-level rise (SLR) scenario combinations.

#### a. Mean summer salinity



# b. Mean spring salinity







SP

# **Distribution Models**

#### Vegetation

Each vegetation species final distribution was modeled through a suite of 1 to 14 top candidate models (Appendix 2). Almost all of the top models included summer salinity. Distribution models had good to excellent predictive accuracy across all species, with AUC ranging between 0.78 and 0.98 (Table 5.). Nine of the fifteen species modeled had AUC > 0.90 (excellent discrimination of presence from absence).

To summarize the estuary wide effects of environmental change on the distributions of vegetation species, we report the mean probability of occurrence throughout the estuary projected by our models. Our models project that plant species will have individual species-specific responses to sea-level rise (Figure 4). For example, the mean probability of occurrence *of Sarcocornia pacifica* increases from current levels across almost all scenarios, while we project *Schoenoplectus acutus* to decrease. While the direction of the change in the projected future probability of occurrence for some species is sensitive to the sediment/sea-level rise scenarios (Figure 4d, 4e), we project most species to have the same directional responses to the different sea-level rise scenarios, with some variation in the magnitude of the response (Figure 4b and 4c).

Some species experience overall declines from current mean probability of occurrence in most future scenarios. *Grindelia stricta, Schoenoplectus acutus, Spartina foliosa*, and the hybrid *Spartina* all decline in the probability of occurrence throughout the Estuary under most future scenarios. However, we note that the hybrid *Spartina* is readily able to colonize mudflat areas, which are not included in our projections, and thus could experience increased probabilities of occurrence over all throughout the estuary. At the same time, species such as *Sarcocornia pacifica* maintain or increase their current mean probabilities of occurrence under most future scenarios, particularly the high sea-level rise scenarios (Figure 4b).

We project the probability of occurrence of the exotic tidal marsh species we modeled, the hybrid *Spartina* and *Lepidium latifolium* to decline from current levels between 2030 and 2050 (Figures 4g and 4h). After 2050, the models project that the mean probability of occurrence for *L. latifolium* will remain relatively stable throughout the Estuary and will remain below current levels through 2110 in all scenarios except for the low sediment/high sea-level rise scenario which projects that the mean probability of occurrence will return to current levels by 2070 and will remain at or above current levels through 2110 (Figure 4h). Projections of the model under the low sediment /high sea-level rise scenario show a dramatic decrease in the overall availability of tidal marsh habitat within Suisun Bay, but what remains is primarily projected to have high probability of *L. latifolium* occurrence.

**Table 5.** Predictive model accuracy for tidal marsh vegetation species as measured by the area under the receiving operator characteristic curve (AUC). AUC ranges from 0 to 1. An AUC of 1 indicates a model which perfectly discriminate species presence from absence and 0.5 means a model discriminates presence from absence no better than random. The most influential variable in the model for each species is also shown.

		Most influential
Species	AUC	variable
Distichlis spicata	0.79	Tidal range
Frankenia salina	0.87	Summer salinity
Grindelia stricta	0.78	Summer salinity
Jaumea carnosa	0.81	Summer salinity
Juncus spp.	0.98	Tidal range
Lepidium latifolium	0.84	Summer salinity
Phragmites australis	0.97	Summer salinity
Sarcocornia pacifica	0.97	Summer salinity
Schoenoplectus acutus	0.96	Summer salinity
Schoenoplectus americanus	0.96	Tidal range
Schoenoplectus californicus	0.95	Summer salinity
Bolboschoenus maritimus	0.94	Summer salinity
Spartina alterniflora	0.97	Tidal range
Spartina foliosa	0.85	Summer salinity
<i>Typha</i> spp.	0.97	Summer salinity

**Figure 4.** The percent change in the mean predicted probability of occurrence of vegetation species across the San Francisco Estuary under current (2010) and future sea-level rise scenarios. The low and high values for sediment scenarios ("Sed Low" and "Sed High") vary by study sub-region (Table 1) and sea-level rise scenarios project a 0.52m and 1.65m increase in sea-level ("SLR Low" and "SLR High" respectively) by 2110. Selected native species shown are *Grindelia stricta* (a), *Sarcocornia pacifica* (b), *Schoenoplectus acutus* (c), *Bolboschoenus maritimus* (d), *Schoenoplectus californicus* (e), and *Spartina foliosa* (f). Exotic species shown are *Spartina alterniflora* (g) and *Lepidium latifolium* (h).





Birds – current distributions and abundance

#### **Clapper Rail**

Probability of occurrence models for Clapper Rail had a cross validated AUC of 0.73 (S.E.  $\pm$  0.01, n = 10). Tidal range was the most important predictor variable (19.2% relative influence, Table 3a.) with higher probability of occurrences found in areas with low tidal range (Figure 5a). Year was the second most influential predictor (15.1 % relative influence, Table 7a) with higher probabilities of occurrence in 2005-2007. Clapper Rails are predicted to be more likely to occur in areas with higher spring salinities (10.05 % relative influence, Figure 5b). The models also found a negative correlation between the mean elevation within a 50m radius and the probability of Clapper Rail occurrence (Figure 5c). Areas with the highest probability of occurrence of Clapper Rails were found in the North Bay; especially around China Camp State Park and Corte Madera.

The cross-validated correlation between the observed and predicted density of Clapper Rails was 0.50 (S.E.  $\pm$  0.05, n = 10). The relative importance of predictor variables in the abundance models was similar to the binomial models. The main difference is that mean elevation had an increased relative importance (14.1%) in the abundance model and is more important than spring salinity (Table 7b). We estimate there are 500 Clapper Rails currently in the Estuary and that San Pablo Bay has slightly more Clapper Rails than San Francisco Bay (300 vs. 200; Table 6).

**Figure 5.** Modeled relationship between Clapper Rail presence/absence (a, c) and abundance (b) and spring salinity (a), tidal range (b) and mean elevation (c) while holding all other variables at their mean values; results from boosted regression tree. The predicted response is scaled to have a mean of 0.


#### **Black Rail**

The occurrence models for Black Rails had the lowest predictive accuracy of any of the bird species modeled with a cross validated AUC of 0.64 (S.E. ± 0.10). Year had the greatest influence on the model with considerable year to year variation in predicted probability of occurrence (19.2.0% relative influence, Table 5a). Spring salinity was the second most influential variable in the occurrence models. Black Rails showed a positive response to increasing distance from the bay, with peak estimated probability of occurrence (controlling for all other variables) occurring between six and ten kilometers from the bay (Figure 6). The distance to urban areas had greater influence, Table 5a). Tidal range (8.8% relative influence) and distance to channel were also influential with Black Rail occurrence predicted to be more likely in areas with a lower tidal range and an increasing distance to channels. Marshes in and along the Petaluma River, the Napa-Sonoma Marshes including Rush Ranch are all predicted to have high probability of occurrence.

The predicted response of Black Rail occurrence to the proportion of low marsh was somewhat unexpected. The BRT predicted that Black Rails would have maximum probability of occurrence in areas with between 10% and 15% of low marsh habitat (Figure 6). As expected, in areas with between 20% to 60% low marsh habitat, the model predicts a very low probability of occurrence. Above the 60% low marsh proportion, the model predicts an increasing probability of occurrence, which is unexpected based on expert knowledge. There are very few areas within the San Francisco Estuary currently with low marsh proportion greater than 70% and the increasing positive response predicted by the model is based on a few, highly influential records. Black Rails are thought to be more associated with mid to high marsh habitat and we suspect that the models are over predicting the probability of occurrence in areas with a high proportion of low marsh. However, due to the low prevalence of areas with extensive low marsh proportion within the San Francisco Estuary today, it is difficult to validate the model.

Black Rail abundance models were similar to the top five most influential variables from the occurrence models (Table 7b), except that we found much less of an influence of salinity in the abundance model. The cross validated correlation between observed and predicted density was 0.18 (S.E.  $\pm$  0.02). The models predict that 12,400 Black Rails occur in the Estuary (Table 6). The population is split with 6,700 predicted to occur in the San Pablo Bay and 5,400 predicted to occur in Suisun (Table 6).

**Figure 6.** Modeled relationship between Black Rail presence/absence and distance to bay (a), tidal range (b) distance to nearest channel (c) and low marsh proportion (d) while holding all other variables at their mean values; results from binomial boosted regression tree. The predicted response is scaled to have a mean of 0.



**Table 6.** Estimated current (2010) abundance for the five tidal marsh focal birds studied. Abundance is estimated for the entire San Francisco Estuary (Total), and bay sub-regions; San Francisco Bay (SF), Suisun Bay (SU) and San Pablo Bay (SP). The lowest (2110 Min) and highest (2110 Max) predicted abundance for the total Estuary at 2110 are also given. Differences between the total and the sum of regional summaries are due to rounding.

Species	SF	SU	SP	Total	2110(Min)	2110(Max)
Black Rail	NA	5,400	6,900	12,400	2,000	30,400
Common Yellowthroat	700	11,800	3,400	15,800	1,100	23,500
Marsh Wren	4,000	34,100	21,700	59,700	3,800	68,700
Song Sparrow	18,000	20,100	60,100	98,200	16,200	198,600
Clapper rail	200	NA	300	500	300	1,200

### **Common Yellowthroat**

The predicted occurrence of Common Yellowthroats was strongly influenced by summer salinity (52.4% relative influence, Table 5a) with higher probabilities of occurrence predicted as salinity decreases. The strong influence of salinity resulted in a pronounced regional gradient in the predicted distribution of Common Yellowthroats. High probabilities of occurrence occur throughout Suisun Bay and Suisun Marsh which has lower salinity than other bay regions (Figures 7). Common Yellowthroats were also predicted to have higher probabilities of occurrence beyond 2 km from the bay. As a result, low probabilities of Common Yellowthroat occurrence were predicted in marshes along the bay edge throughout San Pablo and San Francisco Bays, but with moderately high probability of occurrence in the Napa River, including Pond 2A (Figure 7). Overall the models had excellent predictive ability with cross-validated AUC = 0.93 (S.E.  $\pm 0.01$ , n = 10).

As with the occurrence models, summer salinity was the most influential variable in the abundance models, but was less influential overall (Table 7b). The rankings of the top four most influential variables did not change but higher predicted densities were more clearly associated with areas with low tidal range. The correlation between observed and predicted densities of 0.78 indicates that the abundance models also had relatively high accuracy. The models predicted a total Estuary population of 15,800 Common Yellowthroats, with Suisun having over three times as many predicted Common Yellowthroats as San Pablo Bay, and over 15 times as many as San Francisco Bay (Table 6).

**Figure 7.** Modeled relationship between Common Yellowthroat presence/absence (b) and abundance (a) and summer salinity (a) and distance to bay (b) while holding all other variables at their mean values; results from boosted regression trees. The predicted response is scaled to have a mean of 0.



**Table 7.** The percent relative influence of each predictor variable for each distribution model (a) and abundance model (b) for Black Rails (BLRA), Clapper Rails (CLRA), Common Yellowthroats (COYE), Marsh Wren (MAWR), and Song Sparrows (SOSP). The influence is scaled to add to 100% across all variables. The most important variable for each species is indicated in bold.

A Variable	BLRA	CLRA	COYE	MAWR	SOSP
Bay region	0.2	0.0	0.1	0.4	0.0
Percent Channel	3.0	1.5	1.2	1.7	1.7
Distance to bay	11.51	8.7	10.6	6.4	11.7
Distance to nearest channel	7.5	4.6	0.8	2.5	10.0
Distance to nearest levee	2.9	5.3	1.3	4.1	2.4
Tidal range	8.8	19.2	10.6	21.5	2.6
Mean elevation	3.0	7.5	2.4	3.2	27.2
High marsh proportion	1.6	4.6	2.6	2.7	0.5
Low marsh proportion	4.6	5.1	2.2	2.3	2.0
Mid marsh proportion	2.7	7.0	2.6	4.6	4.1
Elevation variability	5.3	3.2	1.6	2.4	6.3
Salinity	17.57	10.1	52.4	27.0	26.8
Mean slope	4.3	4.8	3.7	6.0	1.0
Таре	NA	0.1	NA	NA	NA
Distance to urban areas	7.5	3.3	2.4	3.7	0.4
Year (factor)	19.19	15.1	5.5	11.5	3.5
B Variable	BLRA	CLRA	COYE	MAWR	SOSP
Bay region	0.0	0.0	0.2	2.5	1.9
Percent Channel	3.14	0.7	1.2	1.9	1.7
Distance to bay	12.0	5.1	10.4	7.3	4.7
Distance to nearest channel	9.9	3.3	1.3	1.9	6.7
Distance to nearest levee	8.1	3.1	4.3	3.5	7.9
Tidal range	7.4	20.6	20.7	18.8	8.8
Mean elevation	3.6	14.1	3.3	4.0	7.8
High marsh proportion	2.2	4.3	2.5	2.5	2.6
Low marsh proportion	4.2	5.0	2.0	2.4	4.6
Mid marsh proportion	2.1	3.5	1.9	3.4	8.6
Elevation variability	7.2	4.0	1.6	2.0	5.7
Salinity	5.5	11.7	38.8	32.5	19.5
Mean slope	5.9	2.9	3.2	4.3	3.7
Таре	NA	0.1	NA	NA	NA
Distance to urban areas	8.1	1.6	2.8	3.1	3.1
Distance to urban areas	0.1	2.0	-		

#### **Marsh Wren**

The predicted distribution of Marsh Wrens was also strongly influenced by summer salinity (Table 5a) with occurrence predicted to be less likely as summer salinity increased. Models also predict that Marsh Wrens are more likely to occur in areas with moderate tidal range (Figure 8). Marsh wren models had excellent predictive accuracy (AUC 0.94, SE  $\pm$  0.01, n = 10). Marsh wrens are predicted to occur in high probability throughout Suisun and in the upper reaches of Napa River and Petaluma River in San Pablo; probabilities in San Francisco Bay are low except for Alviso marshes.

The rankings of the top five most influential variables did not change between the occurrence and abundance models for Marsh Wrens (Table 7). Abundance models for Marsh Wrens had higher predictive accuracy than any other bird species (R = 0.87 between observed and predicted densities, S.E.  $\pm$  0.004, n = 10). Our models predict 59,700 marsh wrens to occur throughout the Estuary. The population in Suisun Bay is predicted to be 64% greater than in San Pablo Bay and almost nine-fold greater than in San Francisco Bay (Table 6). **Figure 8.** Modeled relationship between Marsh Wren abundance (a) presence/absence (b) and summer salinity (a) and tidal range (b) while holding all other variables at their mean values; results from boosted regression tree. The predicted response is scaled to have a mean of 0.



Tidal range (m)

43

#### **Song Sparrow**

Song sparrows are relatively common throughout the Estuary and occurred in approximately 96% of our surveys. Unsurprisingly, the binomial models predicted high probabilities of occurrence throughout the Estuary (mean probability of occurrence throughout the bay = 0.98). The binomial model for Song Sparrow has good accuracy at discriminating presence from absence (AUC = 0.84, S.E. 0.02, n = 10). Mean tidal marsh elevation had the greatest influence on the predicted probability of occurrence of Song Sparrows with higher probabilities of occurrence predicted in areas with mid to high marsh elevations (Table 7a). The models predicted lower probabilities of occurrence in areas with high spring salinity, which was the second most influential variable in the model (Table 7a). Song sparrows are predicted to occur with high probability in most of the Estuary. Areas with lowest predicted probabilities of occurrence include the Napa River region, Hayward marsh/Cogswell marsh, Alviso marsh, and Middle Bair Island.

Mean elevation was less influential in the abundance models for Song Sparrow (Table 7a) while year was the second most influential, highlighting the amount of year to year variation in abundance for this species. Both mean tidal marsh elevation and proportion of mid marsh were moderately influential on the abundance model and predicted higher Song Sparrow densities in areas with moderate amounts of mid-marsh habitat (Figure 9). Song sparrow densities were predicted accurately (R = 0.73, observed vs. predicted densities). While the occurrence models predicted little regional differences variability, the abundance model projected some heterogeneity in abundance across the estuary (Table 6). The abundance of Song Sparrows across the Estuary in 2010 is predicted to be 98,200. The model predicts the highest Song Sparrow abundance in San Pablo Bay (over 60,100).

**Figure 9.** Modeled relationship between Song Sparrow presence/absence (a & b) or abundance (c) and mean elevation within 50 m (a), spring salinity (b), and the proportion of mid-marsh habitat (c) while holding all other variables at their mean values. The predicted response is scaled to have a mean of 0.



### Birds – future distributions and abundance

We found that our projections for future tidal marsh bird populations were sensitive to both the sediment and sea-level rise scenarios we tested. The influence of the sediment and sealevel rise scenarios varied for some species through the time periods studied. For example, the projections for Clapper Rail and Song Sparrow abundance were higher at 2030 and 2050 under the high sediment scenarios than under the low sediment scenarios, reflecting the more rapid gain in tidal marsh habitat with greater sediment availability during this period (Figure 11). Between 2050 and 2090, the influence of the sea-level rise scenarios becomes more important as populations for all species except Clapper Rail are projected to be higher under the low sealevel rise scenario then either sediment scenario with the high sea-level rise scenario (Figure 11). The change in importance of the sea-level rise scenario is coincident with the increasing rates of sea-level rise projected by both scenarios after 2050. In almost all cases, high rates of sea-level rise are projected to have a deleterious effect on tidal marsh bird populations by 2110. For all species, the projected abundance is almost always higher under the high sediment compared to the low sediment scenarios indicating that marsh accretion could buffer the effects of future sea-level rise on tidal marsh birds if sufficient sediment is available (Figure 11, Table 8).

Sediment/Sea-Level Rise Scenario	Black Rail	Clapper Rail	Common Yellowthroat	Marsh Wren	Song Sparrow
Current	12,400	500	15,800	59,700	98,200
Low/Low	21,300	800	15,800	51,100	135,900
High/Low	30,400	1,200	23,500	68,700	198,600
Low/High	2,000	300	1,100	3,800	16,200
High/High	7,800	1,100	3,200	12,300	93,800
Mean	15,400	900	10,900	34,000	111,100
Standard deviation	12,900	400	10,600	31,000	76,500
Mean % change					
2010-2110	24.4%	73.0%	-31.2%	-43.1%	13.16%

**Table 8.** Projected abundance for Black Rails, Clapper Rails, Common Yellowthroats, Marsh Wrens and Song Sparrows at 2010 and 2110 across the San Francisco Estuary given different future sediment x sea-level rise scenarios.

For each species except Clapper Rail, populations throughout the Estuary are projected to be higher under the low sea-level rise scenarios by 2110(Figure 11) mirroring mid-marsh habitat change projections (Stralberg et al. 2011). For Clapper Rails, the differences in projected abundance are more closely related to projected areas of low marsh (Figure 11). In contrast to other species, there were almost no regional differences in the projected change in Clapper Rails abundance across time. Clapper rail models project a decline in populations between 2010 and 2030 in both San Pablo and San Francisco Bay (Figure 10). After 2030, Clapper Rail populations, across regions and all scenarios except the low sediment/high SLR scenario are projected to increase from 2030 levels. For the low sediment scenarios, Clapper Rail populations are projected to remain below 2010 levels through 2070 but increase above 2010 levels between 2070 and 2090 for the low sea-level rise scenario. For the high sediment scenarios, Clapper Rail population projections are expected to remain above 2010 levels throughout the simulation (Figure 11).

The changes in projected Clapper Rail populations are consistent with projected changes in spring salinity and tidal marsh elevations. The decline in projected Clapper Rail abundance is consistent with the decline in spring salinity between 2010 and 2030 (Figure 11 and 3). After 2030, spring salinity is projected to increase, coinciding with increasing Clapper Rail abundance through 2110. The differences between the sediment scenarios are largely due to the effect of sediment on the variation in elevation and percent slope within the study area, the low sediment scenarios had higher marsh elevation variability and percent slope than the high sediment scenarios.

**Figure 10.** The mean estimated abundance across all sediment and sea level rise scenarios for Black Rail, Clapper Rail, Common Yellowthroat, Marsh Wren and Song Sparrow across the total San Francisco Estuary (Total), San Francisco Bay (SF), San Pablo Bay (SP) and Suisun Bay (SU). The error bars show the variation due to future scenarios and indicate ± 1 standard error.



**Figure 11.** The projected percent change from predicted 2010 abundance of Black Rails (BLRA), Clapper Rails (CLRA), Common Yellowthroats (COYE), Marsh Wrens (MAWR) and Song Sparrows (SOSP) for each combination of the sediment/ sea-level rise scenarios. For all species except Clapper Rails, year 2010 predictions are an average of predictions for years 2000-2009, for Clapper Rails the predictions are an average for years 2005-2010. Future projections are made for each 20 year period between 2030-2110.



Most species are projected to experience population declines across the Estuary over the next 100 years under high sea level rise scenarios. For example, Black Rail populations are projected to increase initially and then decline below 2010 levels by 2110 for the high sea-level rise scenarios but remain above 2010 levels for the low sea-level rise scenarios (Figure 11). While Black Rail populations in San Pablo Bay are predicted to remain above 2010 levels from 2030 to 2090, the population in Suisun Bay is projected to remain relatively stable through the same period (Figure 10), following an initial decline between 2010 and 2030. The pattern could reflect a positive response to marsh accretion early in the century which is replaced by a negative response to marsh drowning during the second half of the century as sea–level rise accelerates under both sea–level rise scenarios.

Our projections for Common Yellowthroats and Marsh Wrens to future sediment/ sea-level rise scenarios are very similar to each other (Figure 10, 11). We project that Suisun Bay will have the highest predicted abundance of any of the other Bay regions in the Estuary but also the greatest decline in abundance. Additionally, both species are projected to have much lower abundances for the high sea-level rise scenarios than the low sea-level rise scenarios (Figure 11).

From 2030-2070, Song Sparrow projections for all scenarios except the low sediment/ high sealevel rise are greater than 2010 (Figure 11). The variation due to future scenarios across Song Sparrow projections increases steadily through time, a pattern which is consistent across all species (Figure 11). Song sparrow populations are projected to remain highest in San Pablo Bay relative to other bay regions throughout the next century (Figure 10).

### **CONSERVATION AND MANAGEMENT IMPLICATIONS**

Our results are the first comprehensive, Estuary-wide estimates of areas of concentration for all five tidal marsh bird species. The compilation of data from multiple years (6 years for Clapper Rails; 10 years for the other four tidal marsh bird species) allows more robust inferences about differences in occurrence or in relative density than would be possible from surveys conducted at specific marshes in disparate years due to our ability to more accurately account for the probability of detection and incorporate temporal variation in site occupancy and abundance. Previous field studies of Black Rails in the breeding season have generally not been conducted in San Francisco Bay; our modeling supports the assumption of low likelihood of occurrence. Thus, except for Alviso marshes, the habitat potential of San Francisco Bay marshes with respect to Black Rails appears to be quite limited, including areas that are planned for extensive restoration efforts. Therefore, protection of current and future areas of high concentration, such as Petaluma Marsh and Coon Island in San Pablo Bay and Rush Ranch and Hill Slough in Suisun Bay, is a high priority for this species (Figs. 10 & 12b).

Our results highlight differences among regions of the Estuary, not only in terms of current patterns of distribution and abundance, but also with respect to anticipated changes in population trajectory. Regional differences reflect substantial differences in physical characteristics of the regions, such as reduced tidal range and salinity in Suisun compared with San Pablo and San Francisco Bays. Management of these species needs to be tailored to the regions. For example, population sizes of Common Yellow Throat and Marsh Wren are consistently greater in Suisun Bay and protection of habitat in Suisun ought to be prioritized accordingly based on the importance to these species. Similarly, since we project greater numbers of individuals for most of the species in the high vs. low sediment scenarios, restoration in high sediment areas are more likely to lead to high quality habitat in the future.

Trends projected for the period 2010 to 2030 generally accord well with recent trends observed. Clapper Rails are predicted to show strong declines (~50%) from 2010 to 2030 for the low sediment scenarios; from 2005 to 2010, the species' abundance has declined over 50% (P < 0.001; Liu et al. 2009, PRBO unpublished). Black Rails are predicted to increase in San Pablo Bay; since 1996, their densities have increased at an average annual rate of 4.08% (cumulative increase over 12 years is 61.6%; San Francisco Estuary Indicator Team, 2011; Pitkin and Wood, 2011). The species is not expected to increase in Suisun, and no significant overall trend has been observed from 1996 to 2008. Our models agree with the observed regional differences in the abundance of these species which reflect regional differences in habitat availability and salinity and project these differences to continue into the future. However, our work illustrates the need for regionally specific future efforts to determine whether factors not included in our models also contribute to the regional differences we find.

Our models of species response to future changes in biophysical conditions indicate that there will be substantial changes in the distribution and abundance of plant and bird species throughout the San Francisco Estuary. These changes will be manifested at regional to local scales. For example, as noted above, the direction of population change for tidal marsh birds relative to present day may vary by bay region. At the same time at the local scale, the spatial distribution of individual plant and bird species within a marsh will likely change as species track

suitable biophysical conditions. The management of these systems will require flexibility in order to adapt to the changes which actually occur.

Our models illustrate the value of considering a range of future scenarios. The variation in future predicted bird abundance across the four scenarios tested is high for all species. If we had only chosen to model using the low sea-level rise scenario, our results would predict population increases from current levels by 2110 for most species as opposed to the declines in abundance from current levels predicted for most species using the high sea-level rise scenario. As future projections of sea-level rise are refined, we will be able to narrow the range in estimated future abundance of the species studied. Similarly, we have more confidence in near term predictions given the smaller variation in future sea-level rise projections at 2030 as compared to 2110. Given the variability in future outcomes from our models we recommend the development of adaptation strategies which are flexible enough to change as future projections of sea-level rise and habitat response become more certain. For example, if our high sea-level rise scenario turns out to be too high, restoration is likely to be resilient in throughout much of the estuary allowing more opportunities to initiate restoration projects. On the other hand, if future sea-level rise is projected to be on par with our high scenario, than restoration efforts in high sediment sub-regions as these may be the only areas within the Estuary which are resilient to such high rates of sea-level rise.

The future projections we provide in this report and which are also available online are best used to identify the range of possible responses under the different future scenarios we have tested. The actual value projected at a pixel is unlikely to precisely project the probability of occurrence of a tidal marsh plant or bird. Still, if the models indicate large changes at a site, i.e. the models show highly suitable habitat disappearing due to marsh drowning, then the maps should accurately indicate areas vulnerable to sea-level rise. Below we demonstrate how consensus predictions across scenarios through time can use the range of projections from future scenarios to test the sensitivity of specific locations to the sea-level rise.

### Landscape prioritization

We found striking differences between landscape prioritization results when we considered only current tidal marsh bird projections and when we considered current and future tidal marsh bird projections. Areas along the Napa River and the Point Edith Wildlife refuge were identified as high conservation priority by Zonation when only considering current bird projections (Figure 12a). In contrast, Zonation ranked marshes in South Petaluma Marsh, Mare Island, Corte Madera and on the San Carlos/Redwood City shoreline as high priority conservation targets (Figure 12b) when we included both current and future tidal marsh bird projections in the analysis. We project large proportions of San Francisco and San Pablo Bays to be ranked higher if we consider both current and future projections as opposed to the rankings derived from only current projections (Figure 12c). The opposite was true in Suisun Bay, where rankings were consistently highest using only current predictions (Figures 12a, 12c). Areas where the combined current and future Zonation solution rankings were higher than the current Zonation ranking tend to be located in the higher suspended sediment sub-regions of our analysis (Figure 12c). The high sediment sub-regions are where the future tidal marsh projections are least sensitive to the different sea-level rise scenarios and high Zonation rankings in these areas illustrates how areas which are projected to maintain marsh conditions across scenarios are favored in the analysis.

These results present a conservation dilemma. Should conservation priorities be dictated by current distributions of species or by future models, which have much higher levels of uncertainty? At the same time, our models of tidal marsh ecosystem change project large changes in the availability of habitat over the next 100 years. Conservation efforts which do not account for these changes could prove short sighted. By considering current and all future scenarios together, the Zonation algorithm prioritizes areas which are consistently good while down weighting areas where we have more uncertainty. The Zonation prioritization thus is less influenced by areas of highest projected abundance in the future and is more strongly influenced by areas of relatively high abundance with low uncertainty.

**Figure 12.** Zonation landscape prioritization for maps which consider current projected tidal marsh bird distributions (a) and both current and future tidal marsh distributions (b) and the difference between the two solutions (c). Higher values in the Zonation solutions indicate areas which have higher conservation value (a, b). Higher values in the difference map (c) indicate areas that have high conservation value in the future but not the present while low values mean the areas have high conservation value currently but are less important in the future.



The optimal Zonation landscape prioritization solution, in which areas behind levees were treated equally with other areas, found high ranking areas within existing tidal marshes as well as areas blocked by tidal flow (Figure 13a). The sub-optimal solution, in which areas with blocked or reduced tidal action were removed from the solution first, necessarily identified areas of current tidal marsh with the greatest landscape ranking (Figure 13b). The difference between the optimal and sub-optimal solution highlights the regions in which there is the greatest loss of conservation value from within areas blocked from tidal action by levees (Figure 13c). Large portions of potential tidal marsh habitat within San Pablo Bay standout as areas that have high restoration value for tidal marsh birds. Additionally, throughout the estuary, areas which are currently upland habitat are ranked as valuable by Zonation indicating that high quality tidal marsh bird habitat could be created if we allow marshes to migrate into currently upland habitat by removing levees (Figure 13d). We found 6981.25 ha of existing upland habitat which is currently protected by levees within the top 25% of pixels with the highest replacement costs (Figure 13d).

These maps can be used to identify areas which have the potential to substantially contribute to the habitat availability of tidal marsh species given our future sea-level rise scenarios if levees are breached. Similarly, the maps show areas that are ranked low under either solution, (large portions of Suisun Bay, Figure 13a, b) indicating areas that may be lower priorities for restoration efforts, depending on future sediment availability. Additionally, the maps could be used to evaluate the conservation cost of proposed developments which might permanently remove critical future tidal marsh habitat from the system, particularly in areas of upland elevation that could support future marsh migration.

**Figure 13.** Zonation landscape prioritization considering both current and future for tidal marsh bird species habitat within the San Francisco Estuary (a and b). Higher values indicate more important habitat for conservation. The maps show the rankings for a scenario in which all levees in the estuary were breached (a) and for a scenario in which it is assumed that no levees will be breached and areas behind the levees are removed first (b). The difference (a-b) between the two scenarios illustrates where levees cause the greatest biological loss by preventing the formation of tidal marsh habitat for birds (c), high values indicate greater biological loss from restricting tidal access. Current uplands representing future high priority marsh conservation areas (d) are indicated in red if they are currently blocked by levees.



### **Evaluating restoration projects**

The preceding Zonation prioritization exercises considered all potential tidal marsh habitat as part of the analysis. However it is unrealistic to assume that all existing barriers to tidal action (especially roads) will be removed or altered to support tidal marsh habitat. Therefore we took a more realistic approach by evaluating proposed or ongoing restoration projects to determine which would result in the highest conservation value given our projections. As in the replacement cost analysis above, presenting the results on a per pixel basis provides a fine scale assessment of how implementing restoration projects could contribute to the conservation network (Figure 14a). However, by summarizing the replacement cost by restoration project polygons (Figure 14b, Table 9) we were able to evaluate the benefits of specific restoration projects to a conservation network as a whole. The procedure demonstrated here is easy to implement and is a simple but effective way to evaluate restoration scenarios while incorporating projections of climate change and their uncertainty.

There are several caveats to the Zonation analysis we have presented. The analysis could be improved by including other taxa that could be impacted by sea-level rise as well as those that could realize benefits from restoration projects, most notably shorebirds. A more comprehensive analysis would include projections for as many different taxa as possible to better incorporate the tradeoffs of the loss or gain of different habitat types. We also included restoration projects that were not designed to restore tidal marsh habitat, e.g. Napa River Pond 8 is a managed pond. Our results therefore illustrate the relative ranking of the site with respect to its potential for tidal marsh bird habitat but do not indicate the suitability of the site for restoration to alternative habitat types. Additionally, we only included restoration projects which: 1) had GIS polygons of the project site available and 2) were included in our projections of tidal marsh into the future. Several large restoration projects which he had polygons for, such as Bel Marin Keys, were not included because either there was missing data from the LiDAR base elevation map or, the elevations at the site were lower than was modeled by our marsh accretion scenarios (< -2.4 m MHHW).

Future work should also try to incorporate economic costs directly into the Zonation prioritization. These costs could include, for example, the costs of restoration projects, the cost to purchase land for the conservation network and potentially the costs to human infrastructure due to the loss of ecosystems services such as flood protection. Finally, a low ranking in our analysis does not mean that a restoration project should not be implemented, but rather that other projects may be more likely to contribute to the overall availability of habitat for tidal marsh birds. In fact, we found that all proposed projects would contribute some habitat that was of greater value to the conservation network than is currently available but some projects contribute more.

**Figure 14.** Replacement cost analysis comparing a Zonation analysis in which all potential restoration projects are considered in the solution and when pixels covered by restoration projects are removed first by the algorithm. The results are presented per pixel (a) and summarized for each project polygon by taking an area weighted sum (b). The colors for restoration project polygons indicate the quartiles of the area weighted sum; higher quartiles indicate greater conservation value of the restoration project.



**Table 9.** Rankings of the contribution to an optimal conservation network of currently proposed or existing wetland restoration projects within the San Francisco Estuary. Projects are ranked based on the weighted sum of the per pixel difference in conservation value in the Zonation prioritization when restoration projects are included or forcibly removed first from the solution. Dashed lines separate the quartiles displayed in Figure 14b. This analysis only includes the importance of habitat to tidal marsh birds and does not consider the costs of restoration projects or economic benefits of other ecosystem services which tidal marshes provide. A low rank does not mean that a project was not valuable but rather that the increase in tidal marsh bird habitat was less than what we project that other restoration projects could provide.

Restoration Project	Rank	Restoration Project	Rank	
Bair Island	1	Oro Loma Marsh	37	
Napa River Salt Pond- Camp Two	2	South Bay Salt Pond AB1	38	
San Mateo Baylands	3	Napa River Salt Pond 6	39	
Napa River Salt Pond 8	4	Eden Landing Pond E8A	40	
Lake Merritt	5	South Bay Salt Pond AB2	41	
Candelstick - Yosemite Slough	6	Napa River Salt Pond 2	42	
Cullinan Ranch	7	South Bay Salt Pond E4	43	
Stanley Ranch	8	North Parcel - Leonard Ranch	44	
Skaggs Island	9	Napa River Salt Pond 1	45	
South Bay Salt Pond SF2	10	Sears Point Restoration	46	
Wingo East	11	South Bay Salt Pond E5	47	
South Bay Salt Pond A8S	12	South Bay Salt Pond E6C	48	
River Park	13	Napa River Salt Pond 1A	49	
South Bay Salt Pond R5	14	Albany Marsh Expansion	50	
South Bay Salt Pond E2	15	South Bay Salt Pond E5C	51	
Ringstrom Bay	16	Simmon's Slough	52	
South Bay Salt Pond S5	17	South Bay Salt Pond A2W	53	
South Bay Salt Pond R4	18	Scottsdale Marsh	54	
Napa River Salt Pond 6A	19	Novato Creek	55	
Eden Landing Ecological Reserve	20	South Bay Salt Pond A23	56	
South Bay Salt Pond E8	21	South Bay Salt Pond A22	57	
Napa River Salt Pond 7A	22	Knapp Tract	58	
South Bay Salt Pond E6B	23	Eden Landing Ponds E15	59	
South Bay Salt Pond E1	24	South Bay Salt Pond A3N	60	
Napa River Flood Control Project	25	South Bay Salt Pond E12	61	
South Bay Salt Pond E6A	26	South Bay Salt Pond A5	62	
Berkeley Meadow - Eastshore State Park	27	South Bay Salt Pond E14	63	
Eden Landing Ponds E9	28	South Bay Salt Pond A16	64	
South Bay Salt Pond R2	29	South Bay Salt Pond E1C	65	
South Bay Salt Pond E7	30	South Bay Salt Pond A7	66	
Bahia	31	South Bay Salt Pond A17	67	
Napa River Salt Pond 7	32	South Bay Salt Pond A14	68	
Ravenswood Preserve	33	South Bay Salt Pond A15	69	
South Bay Salt Pond R3	34	Western Stege Marsh	70	
South Bay Salt Pond A1	35	South Bay Salt Pond A13	71	
Oliver Property	36	South Bay Salt Pond A11	72	

# LIMITATIONS OF THE STUDY AND OPPORTUNITIES FOR FUTURE RESEARCH

Values for several parameters used for modeling species distributions were assumed to remain static in future scenarios. At certain spatial scales, the distance to certain features such as the distance to the bay will likely remain unchanged. However other variables such as distance to channels will undoubtedly change. We have attempted to strike a balance between including variables which are hypothesized to be important in limiting the distribution of tidal marsh species and including variables which can plausibly be modeled under future conditions. We believe the static variables we used will remain relatively unchanged in the future making the simplifying assumption warranted. If the variables do change greatly then our results will be less reliable. However, unanticipated changes in features can be readily incorporated into future iterations of our models as new information becomes available

Summer and spring salinity were found to be important in both vegetation and bird distributions. For present day conditions, we used spatial interpolation from point level observations to calibrate our modes. However, salinity can vary considerably within tidal marshes and our spatial interpolations may give an accurate but imprecise estimate of salinity at fine spatial scales. In addition, the future salinity projections we use have considerable uncertainty so our future vegetation and bird projections are somewhat limited by the reliability of salinity models. Our models could be improved by incorporating site-specific measures of salinity into model calibration and improved projections of future salinity.

Our model projections are based on the best regionally-specific estimates of available sediment supply, which is highly uncertain now and in the future. However, the marsh accretion model we use is a one dimensional model which does not account for the transport of sediment between cells. In addition, physical processes such as erosion are not explicitly modeled. As more sophisticated models of sediment transport are developed and the dynamics of sediment between mudflats and the marsh plain are better understood, improved estimates of suspended sediment availability can be used by our model to more accurately model marsh accretion through time.

Our models are based on statistical correlations between the occurrence or abundance of birds and physical characteristics of the environment. The correlations between the occurrence of birds and physical characteristics may indicate a direct relationship in which the species is adapted to a specific range of the physical variable, or simply that a bird may be associated with a plant that co-varies with the physical variable. Our models do not provide a mechanistic link between the species and the physical variables, but the models inform our follow up work. Our forthcoming spatially-implicit, stochastic population models are based on the same sea-level rise scenarios, sediment levels and climate covariates we used here. The models integrate the changes in suitable habitats presented in this report and predict trends of population demographic parameters, particularly population growth rates, on a yearly basis. The spatial, temporal and demographic detail of these models enables us to simulate and evaluate management scenarios.

# **ACKNOWLEDGEMENTS**

This work was supported by grants from the California State Coastal Conservancy and the US Fish and Wildlife Service California Landscape Conservation Cooperative and an anonymous donation. The work was initiated with funding from the San Francisco Bay Fund of the San Francisco Foundation. We thank Hildie Spautz and Mark Herzog for overseeing tidal marsh field data collection from 2000 to 2007. We are indebted to the countless hours of field observations contributed by scores of volunteer and intern biologists since 1995. This is PRBO contribution #1859

## **REFERENCES**

- ACOE. 2009. Incorporating Sea-Level Change Considerations in Civil Works Programs. Engineering Circular #1165-2-211. U.S. Army Corps of Engineers. http://140.194.76.129/publications/eng-circulars/ec1165-2-211/entire.pdf
- Buckland, S. T., D.R. Anderson, K.P. Burnham, J.L. Laake. 1993. *Distance sampling: Estimating Abundance of Biological Populations*. Chapman and Hall, London, reprinted 1999 by RUWPA, University of St. Andrews, Scotland.
- Burnham, K.P., and D. R. Anderson. 2002. Model selection and multimodel inference: a practical information-theoretic approach. 2<sup>nd</sup>. Ed. Springer-Verlag. New York, NY.
- Cayan, D. R., M. Tyree, M. D. Dettinger, H. Hidalgo, T. Das, E. Maurer, P. Bromirski, N. Graham, and R. Flick. 2009. Climate change scenarios and sea level rise estimates for the California 2008 Climate Change Scenarios Assessment.
- Cloern JE et al, 2011. Projected evolution of California's San Francisco Bay-Delta-River system in a century of climate change. In preparation.
- Costanza, R., R. d' Arge, R. de Groot, S. Farber, M. Grasso, B. Hannon, K. Limburg, S. Naeem, R. O'Neill, J. Paruelo, R. G. Raskin, P. Sutton, and M. van den Belt. 1997. The Value of the world's ecosystem services and natural capital. Nature 387:253-260.
- Craft, C., J. Clough, J. Ehman, S. Joye, R. Park, S. Pennings, H. Guo, and M. Machmuller. 2009. Forecasting the effects of accelerated sea-level rise on tidal marsh ecosystem services. Frontiers in Ecology and the Environment **7**:73-78.
- Efron, B. 1983. Estimating the error rate of a prediction rule: Improvement on cross-validation. J. of the American Statistical Association, **78**: 316-331.
- Elith, J. and C. H. Graham. 2009. Do they/ how do they/ Why do they differ? on finding reasons for differeing performance of species distribution models. Ecography **32**:66-77.
- Elith, J., J. Leathwick, and T. Hastie. 2008. A working guide to boosted regression. Journal of Animal Ecology **77**:802-813.

ESRI (Environmental Systems Resource Institute). 2009. ArcMap 9.3.1. Redlands, California.

Goals Project. 1999. Baylands ecosystem habitat goals. A report of habitat recommendations prepared by the San Francisco Bay Area Wetlands Ecosystems Goals Project. Joint publication of the U. S. Environmental Protection Agency, San Francisco, CA, and San Francisco Bay Regional Water Quality Control Board, Oakland, CA. http://www.sfei.org/node/2123

- Goals Project. 2000. Baylands ecosystem species and community profiles: Life histories and environmental requirements of key plants, fish, and wildlife. Prepared by the San Francisco Bay Area Wetlands Ecosystem Goals Project. P.R. Olofson, ed. San Francisco Bay Regional Water Quality Control Board, Oakland, Calif. http://www.sfestuary.org/pdfs/speciescommunity/Species\_and\_Community\_Profiles%5BPart1%5D.pdf
- Greenberg, R., J. Maldonado, S. Droege, and M. V. McDonald. 2006a. Tidal marshes: a global perspective on the evolution and conservation of their terrestrial vertebrates. BioScience **56**:675-685
- Hastie, T., Tibshirani, R., and J. Friedman. 2001. The elements of statistical learning. Springer Series in Statistics. New York, NY.

- IPCC. 2007. Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.
- Kirwin, M. L. and G. R. Guntenspergen. 2009. Accelerated sea-level rise- a response to Craft *et al*. Frontiers in Ecology and the Envrionment. **7**:126-127.
- Kirwan, M. L., G. R. Guntenspergen, A. D'Alpaos, J. T. Morris, S. M. Mudd, and S. Temmerman. 2010. Limits on the adaptability of coastal marshes to rising sea level. Geophysical Research Letters **37**:L23401.
- Knowles, N. 2010. Potential Inundation Due to Rising Sea Levels in the San Francisco Bay Region. San Francisco Estuary and Watershed Science, **8**: 1:19.
- Liu, C., P.M. Berry, T. P. Dawson, and R.G. Pearson. 2005. Selecting thresholds of occurrence in the prediction of species distributions. Ecography, **28**: 385-393.
- L. Liu, P. Abbaspour, M. Herzog, N. Nur, and N. Warnock. 2007. San Francisco Bay Tidal Marsh Project Annual Report 2006: Distribution, abundance, and reproductive success of tidal marsh birds. PRBO Conservation Science, Petaluma, CA.

http://www.prbo.org/cms/docs/wetlands/PRBOTidalMarsh2006AnnualReport.pdf Moilanen, A. 2007. Landscape Zonation, benefit functions and target-based planning: Unifying reserve selection strategies. Biological Conservation 134:571-579.

- Moilanen, A., A. Arponen, J. N. Stokland, and M. Cabeza. 2009. Assessing replacement cost of conservation areas: How does habitat loss influence priorities? Biological Conservation 142:575-585.
- Pitkin, M. and Wood, J. (Editors). 2011 The State of the Birds, San Francisco Bay. PRBO Conservation Science and the San Francisco Bay Joint Venture.
- Rahmstorf, S. 2007. A Semi-Empirical Approach to Projecting Future Sea-Level Rise. Science 315:368-370.
- R Development Core Team. 2010. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. <u>http://www.R-project.org</u>
- Royle, J. A., J. D. Nichols, and M. Kery. 2005. Modeling occurrence and abundance of species when detection is imperfect. Oikos 110:353-359.

Spautz, H., N. Nur, D. Stralberg, and Y. Chan. 2006. Multiple-scale habitat relationships of tidalmarsh breeding birds in the San Francisco Bay estuary. Studies in Avian Biology 32:247–269.

- Shuford, W.D. and Gardali, T. editors. 2008. California Bird Species of Special Concern: A ranked assessment of species, subspecies, and distinct populations of birds of immediate conservation concern in California. Studies of Western Birds 1. Western Field Ornithologists, Camarillo, California, and California Department of Fish and Game.
- Stralberg, D., M. P. Herzog, N. Nur, K. A. Tuxen, and M. Kelly. 2010. Predicting avian abundance within and across tidal marshes using fine-scale vegetation and geomorphic metrics. Wetlands 30:475-487.
- Stralberg D, Brennan M, Callaway JC, Wood JK, Schile LM, et al. (2011) Evaluating Tidal Marsh Sustainability in the Face of Sea-Level Rise: A Hybrid Modeling Approach Applied to San Francisco Bay. PLoS ONE 6(11): e27388. doi:10.1371/journal.pone.0027388
- Takekawa, J. Y., I. Woo, H. Spautz, N. Nur, J. L. Grenier, K. Malamud-Roam, J. C. Nordby, A. N. Cohen, F. Malamud-Roam, and S. E. Wainwright-De La Cruz. 2006. Environmental threats to

tidal marsh vertebrates in the San Francisco Bay estuary. Studies in Avian Biology 32:176-197.

- Thomas, L. J.L. Laake, E. Rexstad, S. Strindgerg, F.F.C. Marques, S. T. Buckland, D.L., Borchers, D.R. Anderson, K.P. Burnham, M.L. Burt, S. L. Pollard, J.H. Bishop, T.A. Marques. 2009. Distance 6.0. Research Unit for Wildlife Population Assessment, University of St. Andrews, UK. http://www.ruwpa.st-and.ac.uk/distance/
- U.S. Fish and Wildlife Service. 2009. Draft Recovery Plan for Tidal Marsh Ecosystems of Northern and Central California. Sacramento, California. xviii + 636 pp.
- Vermeer, M. and S. Rahmstorf. 2009. Global sea level linked to global temperature. Proceedings of the National Academy of Sciences.
- Wright, S. A. and D. H. Schoellhamer. 2004. Trends in the Sediment Yield of the Sacramento River, California, 1957 2001. San Francisco Estuary and Watershed Science 2.

## **APPENDICES**

**Appendix 1.** List of meetings, workshops and conferences where staff have presented the results of this study and the online decision supprt tool.

- 1. SF Bay Joint Venture Restoration Committee
- 2. Bay-Delta Conference, Sediment Management Workshop
- 3. California Vulnerability and Adaptation Study
- 4. SF Bay Joint Venture Management Board
- 5. North Bay Managers Meeting
- 6. East Bay Regional Parks District
- 7. PACLIM conference 2011
- 8. California Landscape Conservation Cooperative Open House, 2011
- 9. State of the Estuary Conference, 2011
- 10. Will they Sink or Swim? A Workshop on Management, Monitoring, and Modeling of California's Estuarine Marshes Under Sea-level Rise
- 11. North Bay Climate Adaptation Imitative Summit, Fall 2011
- 12. South Bay Salt Pond Management Team, Fall 2011
- 13. American Geophysical Union, Fall meeting 2011.
- 14. BCDC, 2010
- 15. H2O- Headwaters to Ocean Conference, San Diego, May 2011
- 16. San Pablo Bay NWR, 2011

**Appendix 2** Top generalized additive models (GAM) predicting vegetation species' occurrence, selected based on AIC. All models within two AIC units of the model with the lowest AIC were retained for further modeling.

Species	Rank	Model	AIC
Distichlis spicata	1	salinsum + distbay + meanhhw + slope + mhhw10maj*salinsum	618.75
	2	salinsum + distchan + distbay + meanhhw + slope + mhhw10maj*salinsum	619.24
		salinsum + distbay + meanhhw + mhhw10maj + slope +	
	4	mhhw10maj*salinsum	619.52
		salinsum + distchan + distbay + meanhhw + mhhw10maj + slope +	
	5	mhhw10maj*salinsum	620.16
	6	salinsum + distchan + distbay + meanhhw + mhhw10maj + slope	620.69
Species	Rank	Model	AIC
Frankenia salina	1	salinsum + channelpercent + distlevee + distbay + mhhw10maj + mhhwsd + mhhw10maj*salinsum	425.43
		salinsum + channelpercent + distlevee + distbay + meanhhw + mhhw10maj + mhhwsd +	
	2	mhhw10maj*salinsum	425.43
Species	Rank	Model	AIC
Grindelia stricta	1	salinsum + distlevee + distbay + meanhhw + slope + mhhw10maj*salinsum	598.36
	2	salinsum + distlevee + distbay + meanhhw + mhhwsd + slope + mhhw10maj*salinsum	598.88
Species	Rank	Model	AIC
Jaumea carnosa	1	salinsum + distchan + distlevee + distbay + meanhhw + mhhw10maj + mhhwsd	588.03
	2	salinsum + distchan + distlevee + distbay + meanhhw + mhhw10maj + slope	589.33
	3	salinsum + distchan + distlevee + distbay + meanhhw + mhhw10maj + mhhwsd + slope	589.42
		salinsum + distchan + channelpercent + distlevee + distbay + meanhhw + mhhw10maj + mhhwsd	+
	4	slope	589.95
Species	Rank	Model	AIC
Juncus spp.	1	salinsum + distlevee + distbay + meanhhw + mhhw10maj*salinsum	159.38
	2	salinsum + distlevee + distbay + meanhhw	160.43
Species	Rank	Model	AIC
Lepidium latifolium	1	salinsum + channelpercent + distlevee + distbay + meanhhw + slope	465.64

	2	salinsum + distchan + channelpercent + distlevee + distbay + meanhhw + slope	467.4
Species	Rank	Model	AIC
Phragmites australis	1	salinsum + distlevee + slope	132.5
	2	salinsum + distlevee + distbay + slope	132.58
	3	salinsum + channelpercent + distlevee + distbay + slope	133.06
	4	salinsum + distlevee + mhhwsd + slope	133.18
	5	salinsum + distlevee + mhhw10maj + slope	133.48
	6	salinsum + distlevee + distbay + mhhw10maj + slope	133.65
	7	salinsum + distlevee + mhhwsd	133.85
Species	Rank	Model	AIC
Sarcocornia pacifica	1	salinsum + mhhw10maj	145.51
	2	salinsum + distlevee + mhhw10maj	15.9
	3	salinsum + distbay + mhhw10maj	145.99
	4	salinsum + mhhw10maj + mhhw10maj*salinsum	146.97
Species	Rank	Model	AIC
Schoenoplectus			
acutus	1	salinsum + distbay + mhhwsd	202.13
	2	salinsum + distchan + distbay + mhhw10maj	202.24
	3	salinsum + distbay + mhhw10maj + mhhwsd	202.31
	4	salinsum + distbay + mhhw10maj	202.43
	5	salinsum + distbay + mhhwsd + slope	202.75
	6	salinsum + distchan + distbay + mhhwsd + slope	23.3
	7	salinsum + distchan + distbay + mhhw10maj + mhhwsd	203.36
	8	salinsum + distbay	203.61
	9	salinsum + distchan + distbay + mhhwsd	203.62
	10	salinsum + distchan + distbay	203.73
	11	salinsum + distchan + distbay + meanhhw + mhhw10maj + mhhwsd + slope	203.93
	12	salinsum + distbay + meanhhw + mhhwsd + slope	204.05
Species	Rank	Model	AIC

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4salinsum + distchan + channelpercent + distbay + mhhw10maj + mhhwsd241.415salinsum + distchan + distlevee + distbay + mhhwsd + mhhw10maj*salinsum241.49SpeciesRankModelAlCBolboschoenus maritimus1salinsum + distchan + distlevee + distbay + meanhhw + mhhw10maj + mhhw10maj *salinsum372.422salinsum + distchan + distbay + meanhhw + mhhw10maj + mhhw10maj *salinsum373.433salinsum + distchan + distbay + meanhhw + mhhw10maj + slope + mhhw10maj *salinsum374.36SpeciesRankModelAlCSpeciesRankModelAlCSpeciesRankModelAlCSpecies1salinsum + distchan + channelpercent + distbay + meanhhw + slope + mhhw10maj *salinsum374.36Species1salinsum + distchan + channelpercent + distbay + meanhhw + slope + mhhw10maj *salinsum447.4SpeciesRankModelAlCSpartina foliosa1salinsum + channelpercent + meanhhw + mhhw10maj *salinsum176.722salinsum + channelpercent + meanhhw + mhhw10maj *salinsum176.723channelpercent + distbay + meanhhw + mhhw10maj *salinsum176.914salinsum + distchan + channelpercent + meanhhw + mhhw10maj *salinsum177.025channelpercent + distbay + meanhhw + mhhw10maj *salinsum177.036salinsum + channelpercent + distbay + meanhhw + mhhw10maj *salinsum177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj *salinsum177.29		2		
5salinsum + distchan + distlevee + distbay + mhhwsd + mhhw10maj*salinsum241.49SpeciesRankModelAlCBolboschoenus maritimus1salinsum + distchan + distlevee + distbay + meanhhw + mhhw10maj + mhhw10maj*salinsum372.422salinsum + distchan + distbay + meanhhw + mhhw10maj + mhhw10maj*salinsum373.433salinsum + distchan + distbay + meanhhw + mhhw10maj + slope + mhhw10maj*salinsum374.36SpeciesRankModelAlCSpeciesRankModelAlCSpeciesRankModelAlCSpecies1salinsum + distchan + channelpercent + distbay + meanhhw + slope + mhhw10maj*salinsum447.4SpeciesRankModelAlCSpartina foliosa1salinsum + channelpercent + meanhhw + mhhw10maj176.592salinsum + channelpercent + meanhhw + mhhw10maj176.723channelpercent + distbay + meanhhw + mhhw10maj176.914salinsum + distchan + channelpercent + meanhhw + mhhw10maj177.025channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.025channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29		3	salinsum + distchan + channelpercent + distlevee + distbay + slope + mhhw10maj*salinsum	241.33
SpeciesRankModelAICBolboschoenus maritimus1salinsum + distchan + distlevee + distbay + meanhhw + mhhw10maj + mhhw10maj*salinsum372.422salinsum + distchan + distbay + meanhhw + mhhw10maj + mhhw10maj*salinsum373.433salinsum + distchan + distbay + meanhhw + mhhw10maj + slope + mhhw10maj*salinsum374.36SpeciesRankModelAICSpartina foliosa1salinsum + distchan + channelpercent + distbay + meanhhw + slope + mhhw10maj*salinsum447.4SpeciesRankModelAICSpartina foliosa1salinsum + distchan + channelpercent + distbay + meanhhw + slope + mhhw10maj*salinsum447.4SpeciesRankModelAICSpartina hybrid1salinsum + channelpercent + meanhhw + mhhw10maj176.722salinsum + channelpercent + meanhhw + mhhw10maj*salinsum176.723channelpercent + distbay + meanhhw + mhhw10maj176.914salinsum + distchan + channelpercent + meanhhw + mhhw10maj177.025channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.066salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29		4	salinsum + distchan + channelpercent + distbay + mhhw10maj + mhhwsd	241.41
Bolioschoenus maritimus3 salinsum + distchan + distlevee + distbay + meanhhw + mhhw10maj + mhhw10maj*salinsum372.42 373.43 373.43 3 salinsum + distchan + distbay + meanhhw + mhhw10maj + mhhw10maj*salinsum372.42 373.43 373.43 373.43 373.43 3 salinsum + distchan + distbay + meanhhw + mhhw10maj + slope + mhhw10maj*salinsum372.42 373.43 373.43 373.43 374.36SpeciesRankModelAICSpaciesRankModelAICSpeciesRankModelAICSpaciesRankModelAICSpaciesRankModelAICSpartina foliosa1salinsum + distchan + channelpercent + distbay + meanhhw + slope + mhhw10maj*salinsum447.4SpeciesRankModelAICSpartina hybrid1salinsum + channelpercent + meanhhw + mhhw10maj176.592salinsum + channelpercent + meanhhw + mhhw10maj*salinsum176.723channelpercent + distbay + meanhhw + mhhw10maj176.914salinsum + distchan + channelpercent + meanhhw177.025channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.066salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29		5	salinsum + distchan + distlevee + distbay + mhhwsd + mhhw10maj*salinsum	241.49
maritimus1salinsum + distchan + distlevee + distbay + meanhhw + mhhw10maj + mhhw10maj *salinsum372.422salinsum + distchan + distbay + meanhhw + mhhw10maj + mhhw10maj *salinsum373.433salinsum + distchan + distbay + meanhhw + mhhw10maj + slope + mhhw10maj *salinsum374.36SpeciesRankModelAlCSpeciesRankModel447.4SpeciesRankModel447.4Speciessalinsum + distchan + channelpercent + distbay + meanhhw + slope + mhhw10maj *salinsum447.4SpeciesRankModelAlCSpartina hybrid1salinsum + channelpercent + meanhhw + mhhw10maj *salinsum176.792salinsum + channelpercent + meanhhw + mhhw10maj *salinsum176.723channelpercent + distbay + meanhhw + mhhw10maj *salinsum176.914salinsum + distchan + channelpercent + meanhhw + mhhw10maj *salinsum177.025channelpercent + distbay + meanhhw + mhhw10maj *salinsum177.066salinsum + channelpercent + distbay + meanhhw + mhhw10maj *salinsum177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj *salinsum177.29	Species	Rank	Model	AIC
2salinsum + distchan + distbay + meanhhw + mhhw10maj + mhhw10maj*salinsum373.433salinsum + distchan + distbay + meanhhw + mhhw10maj + slope + mhhw10maj*salinsum374.36SpeciesRankModelAlCSpeciesSpeciesSpeciesSpecies	Bolboschoenus			
3salinsum + distchan + distbay + meanhhw + mhhw10maj + slope + mhhw10maj*salinsum374.36SpeciesRankModelAlCSpeciesRankSalinsum + channelpercent + meanhhw + mhhw10maj*salinsum176.59SpeciesSpeciesSalinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.02SpeciesSpeciesSalinsum + channelpercent + distbay + meanhhw + mhhw10maj *salinsum177.13 <td>maritimus</td> <td></td> <td></td> <td></td>	maritimus			
SpeciesRankModelAICSpartina foliosa1salinsum + distchan + channelpercent + distbay + meanhhw + slope + mhhw10maj*salinsum447.4SpeciesRankModelAICSpartina hybrid1salinsum + channelpercent + meanhhw + mhhw10maj176.592salinsum + channelpercent + meanhhw + mhhw10maj*salinsum176.723channelpercent + distbay + meanhhw + mhhw10maj176.914salinsum + distchan + channelpercent + meanhhw177.025channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.026salinsum + channelpercent + distbay + meanhhw + mhhw10maj177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29		2		
Spartina foliosa1salinsum + distchan + channelpercent + distbay + meanhhw + slope + mhhw10maj*salinsum447.4SpeciesRankModelAICSpartina hybrid1salinsum + channelpercent + meanhhw + mhhw10maj176.592salinsum + channelpercent + meanhhw + mhhw10maj*salinsum176.723channelpercent + distbay + meanhhw + mhhw10maj176.914salinsum + distchan + channelpercent + meanhhw177.025channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.066salinsum + channelpercent + distbay + meanhhw + mhhw10maj177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29		3	salinsum + distchan + distbay + meanhhw + mhhw10maj + slope + mhhw10maj*salinsum	374.36
SpeciesRankModelAICSpartina hybrid1salinsum + channelpercent + meanhhw + mhhw10maj176.592salinsum + channelpercent + meanhhw + mhhw10maj*salinsum176.723channelpercent + distbay + meanhhw + mhhw10maj176.914salinsum + distchan + channelpercent + meanhhw177.025channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.026salinsum + channelpercent + distbay + meanhhw + mhhw10maj177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29	Species	Rank	Model	AIC
Spartina hybrid1salinsum + channelpercent + meanhhw + mhhw10maj176.592salinsum + channelpercent + meanhhw + mhhw10maj*salinsum176.723channelpercent + distbay + meanhhw + mhhw10maj176.914salinsum + distchan + channelpercent + meanhhw177.025channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.026salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29	Spartina foliosa	1	salinsum + distchan + channelpercent + distbay + meanhhw + slope + mhhw10maj*salinsum	447.4
2salinsum + channelpercent + meanhhw + mhhw10maj*salinsum176.723channelpercent + distbay + meanhhw + mhhw10maj176.914salinsum + distchan + channelpercent + meanhhw177.025channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.066salinsum + channelpercent + distbay + meanhhw + mhhw10maj177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29	Species	Rank	Model	AIC
3channelpercent + distbay + meanhhw + mhhw10maj176.914salinsum + distchan + channelpercent + meanhhw177.025channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.066salinsum + channelpercent + distbay + meanhhw + mhhw10maj177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29	S <i>partina</i> hybrid	1	salinsum + channelpercent + meanhhw + mhhw10maj 176.59	
4salinsum + distchan + channelpercent + meanhhw177.025channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.066salinsum + channelpercent + distbay + meanhhw + mhhw10maj177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29		2	salinsum + channelpercent + meanhhw + mhhw10maj*salinsum	176.72
5channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.066salinsum + channelpercent + distbay + meanhhw + mhhw10maj177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29		3	channelpercent + distbay + meanhhw + mhhw10maj	176.91
6salinsum + channelpercent + distbay + meanhhw + mhhw10maj177.137salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum177.29		4	salinsum + distchan + channelpercent + meanhhw	177.02
7 salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum 177.29		5	channelpercent + distbay + meanhhw + mhhw10maj*salinsum	177.06
		6	salinsum + channelpercent + distbay + meanhhw + mhhw10maj	177.13
8 salinsum + channelpercent + meanhhw + mhhw10maj + mhhw10maj*salinsum 177.31		7	salinsum + channelpercent + distbay + meanhhw + mhhw10maj*salinsum	177.29
		8	salinsum + channelpercent + meanhhw + mhhw10maj + mhhw10maj*salinsum	177.31

Typha spp.	1	salinsum + mhhw10maj + slope	225.92
Species	Rank	Model	AIC
	14	salinsum + distbay + meanhhw + mhhw10maj + mhhw10maj*salinsum	178.47
	13	salinsum + distbay + meanhhw	178.44
	12	salinsum + channelpercent + distbay + meanhhw + mhhw10maj + mhhw10maj*salinsum	178.14
	11	salinsum + distchan + distbay + meanhhw	177.99
	10	salinsum + distchan + channelpercent + distbay + meanhhw	177.64
	9	salinsum + channelpercent + distbay + meanhhw	177.63