

The Conservation of Tidal Marsh Birds: *Guiding action at the intersection of our changing land and seascapes*



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ON THE COVER

Edwin B. Forsythe National Wildlife Refuge, New Jersey, 2012

Photograph by: Becky Kern

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I. Executive Summary

Major Findings

1. Marshes from New Jersey to Virginia support greater abundances of Species of Greatest Conservation Need (SGCN) relative to the smaller marshes of New England and New York, including Clapper Rail, Willet, American Black Duck, Saltmarsh Sparrow, and Seaside Sparrow.
2. The density of some species (e.g. Saltmarsh and Seaside sparrows) is highest in the north, however, and marshes in New York and New England support approximately 30% of the global breeding population of Saltmarsh Sparrows.
3. Black Rail detections were too infrequent (10 detections over two years) to estimate abundance or trends, despite call-back surveys across USFWS Region 5, indicating a complete collapse of these Mid-Atlantic populations.
4. On average, tidal-marsh specialists have declined across New England and USFWS Region 5 as a whole over the last two decades.
5. For Saltmarsh Sparrows, these declines are most severe on marshes with tidal restrictions, although the trend remains across all tidal marsh specialists even when excluding Saltmarsh Sparrow.
6. Within Connecticut (the only state where historical nesting data were available), nest density is also declining for Saltmarsh Sparrows, Seaside Sparrows, and Clapper Rail, with Saltmarsh Sparrows showing the strongest decline. The declines can be explained by increases in rates of nest flooding since 2002.
7. Seasonal reproductive success (incorporating nest success and renesting rates) for Seaside Sparrows declined from south to north within USFWS Region 5. Nelson's Sparrow reproductive success exhibited no large-scale patterns across the survey area but was considerably higher at the single well-sampled upriver marsh compared to multiple coastal sites.
8. Saltmarsh Sparrow seasonal reproductive success was highly variable across the range and is driven more strongly by local rather than regional patterns. Nest flooding was locally variable across the range, but predation rates increased to the south.
9. Population growth rates for Saltmarsh Sparrow are consistently negative across much of the species range. Current projections suggest a >90% reduction in population within 50 years, putting the species on a clear trajectory towards extinction. Demographic models also suggest that Nelson's and Seaside Sparrows will experience range contractions over this time frame.

Detailed Summary

Tidal marshes form the dominant transition zone between terrestrial and marine communities in eastern North America. These marshes are important globally as reservoirs of biodiversity, with 56% of the endemic saltmarsh species or subspecies in the world. Tidal marshes also perform many key services to humans, absorbing the energy of ocean storms, improving water quality, and providing nutrients and nurseries for marine food webs. North America, therefore, plays a critical role in the conservation of the ecosystem's global flora and fauna, while coastal towns and cities benefit directly from their local marshes. The proximity to coastal communities, however, has contributed to a suite of impacts that have degraded ecosystem quality. There are

no pristine tidal marshes left in the United States. Sea-level rise, also is responsible for a large and emerging threat to the persistence of the remaining ecosystem.

Endemic bird taxa are at extreme risk to these changes, and the combination of habitat loss and reported reductions in vital rates from flooding suggests that further sea-level increases could push bird populations to a threshold beyond which rapid declines are likely. The Saltmarsh Sparrow (*Ammodramus caudacutus*) is listed as globally Vulnerable by the International Union for Conservation of Nature, and both King (*Rallus elegans*) and Black rail (*Laterallus jamaicensis*) are listed as Near Threatened. Overall, thirteen species on the North American Bird Conservation Initiative's (NABCI) Watch List regularly use tidal marshes, and 26 bird species that breed in or use these habitats during summer are listed as Species of Greatest Conservation Need (SGCN) by states across the Northeast US.

This project focuses on the state of tidal marsh bird populations in the coastal zone from Virginia to Maine, encompassing habitat in ten states. In this report, we detail work conducted to address the needs of each state as expressed in State Wildlife Action Plans (SWAPs). We estimated the current abundances of 23 wetland bird species using the tidal marsh in 1,780 survey locations from Maine to Virginia and estimated historical change in these populations since 1994 using data from 3,064 survey locations over the same region. Further, we studied the reproduction of five focal endemics (Saltmarsh Sparrow, Nelson's Sparrow – *A. nelsoni*, Seaside Sparrow – *A. maritimus*, Clapper Rail – *Rallus crepitans*, and Willet – *Tringa semipalmata*) and modeled adult survival and population viability for the three songbirds using data from 23 demographic plots spread across seven states (ME, NH, MA, RI, CT, NY, NJ). We then used this information to pilot two different approaches for prioritizing conservation actions at a state level.

Current Species Abundances – We used a Bayesian network approach to predict distribution and population estimates for our five focal species (numbers reported in the body of the report). Our results show that overall, large expansive marsh complexes from Coastal New Jersey to Eastern Chesapeake Bay supported the majority of Clapper Rail, Willet, Saltmarsh Sparrow, and Seaside Sparrow individuals. Species were most common in Long Island (Saltmarsh and Seaside sparrows), Delaware Bay (Clapper Rail), and Coastal Delmarva (Willet). New Jersey supported the greatest abundance among all of the states for three species (Willet, Saltmarsh Sparrow, and Seaside Sparrow), and Virginia supported half of the region's Clapper Rails. Nelson's Sparrows were distributed from Cape Ann, Massachusetts north into Maine, but occurred at the greatest density and abundance in Coastal Maine. Spring migrants were detected further south; however, the region from Cape Ann to Casco Bay, Maine supported 30% of the population, indicating that patches at range peripheries can support substantial local populations.

Generally, the marshes of more southern states (NJ, DE, MD, and VA) in the region, which contain larger expanses of tidal marsh, supported greater abundances of SGCN individuals than those of northern states (NY, CT, RI, MA, NH, and ME). American Black Duck (*Anas rubripes*), Great Blue Heron (*Ardea herodias*), Glossy Ibis (*Plegadis falcinellus*), Great Egret (*Ardea alba*), Little Blue Heron (*Egretta caerulea*), Least Bittern (*Ixobrychus exilis*), Forster's Tern (*Sterna forsteri*), Laughing Gull (*Leucophaeus atricilla*), and Swamp Sparrow (*Melospiza georgiana*) had their greatest abundances in states from New Jersey south. Black-crowned (*Nycticorax*

nycticorax) and Yellow-crowned night-herons (*Nyctanassa violacea*) had their greatest abundances in New York and New Jersey. Common Tern (*S. hirundo*) was most abundant in the marshes of New York, New Jersey, Massachusetts, and Virginia. Notably, Virginia tidal marshes support the greatest abundance of Virginia Rail, suggesting that there may be a hitherto undescribed endemic tidal marsh population in this region. New York supported more than 50% of one species' tidal marsh population (Black-crowned Night-Heron) as well as a large proportion of Common Terns; New Jersey supported more than 50% of two species' tidal marsh populations (Great Egret and Yellow-crowned Night-Heron) and large proportions of the Common Terns, Laughing Gulls, Little Blue Herons, Marsh Wrens (*Cistothorus palustris*), Snowy Egrets (*Egretta thula*), Tricolored Herons (*Egretta tricolor*), and Willow Flycatchers (*Empidonax traillii*) that use coastal marshes; Delaware marshes supported large populations of Common Yellowthroat (*Geothlypis trichas*), Great Blue Heron and Willow Flycatcher; Maryland supported more than 50% of the coastal marsh populations of five species (American Black Duck, Glossy Ibis, Least Bittern, Swamp Sparrow, and Virginia Rail) and large numbers of Common Yellowthroat, Forster's Tern, Great Blue Heron, Marsh Wren, and Snowy Egret; Virginia marshes supported large populations of Forster's Tern, Laughing Gull, Little Blue Heron, and Tricolored Heron. Overall SGCN species richness ranged from 14 in New Hampshire to 25 in New Jersey.

Overall, our findings highlight the importance of expansive marshes to tidal marsh bird populations and our ability to maintain these areas as viable habitats will likely determine the future persistence of these species in the Northeast. Despite their smaller extent, however, marshes on Long Island and northward also are important for the tidal marsh birds considered most at risk from accelerated sea level rise. For instance, we estimated that almost 30% (18,000 individuals) of the global population of Saltmarsh Sparrows occurs in New England and Long Island marshes. While marshes north of Long Island have fewer opportunities for marsh transgression than those farther south, parts of this region are experiencing lower rates of sea level rise than the Mid-Atlantic and may become a stronghold of Saltmarsh Sparrow in the future.

Historical Changes – We found significant changes for six of the 19 SGCN for which we modeled abundance over our 18-year period of observation (1994 – 2012). Generalist species that use other habitats in addition to salt marshes, tended to fare better. Clapper Rail, Nelson's Sparrow, and Saltmarsh Sparrow – all tidal marsh specialist species – showed significant declines, and the two sparrow species showed similar rates of decline within our more robust New England trend analysis. Three species (Great Egret, Glossy Ibis, Common Yellowthroat) showed consistent increases over the period, while populations of the remaining 13 species appeared stable. Saltmarsh Sparrows in particular showed consistent declines at multiple spatial scales: We detected significant declines in three of the four long-term refuge datasets (Rachel Carson, Parker River, and Bombay Hook NWRs), in two of the five New England states (Maine and Connecticut), in two of the three New England subregions (Coastal Maine and Cape Cod to Casco Bay), and across New England and USFWS Region 5 as a whole. We detected no population increases at any scale. Across the entire region we estimate that Saltmarsh Sparrows experienced the greatest annual population change for any of our five focal species, a decline at the rate of 9.0% annually.

Marshes with tidal restrictions are experiencing steeper declines both for Saltmarsh Sparrows and across our five focal species as a group. In fact, tidal restrictions supersede sea-level rise as the dominant driver of community decline. On average, tidal-marsh specialists are declining in locations that are tidally restricted, but are maintaining their populations in marshes that have no road crossings affecting tidal flow. We suggest that restrictions change the hydrology of marshes and prevent the maintenance of marsh elevation in the face of sea level rise.

Reproduction – Across our 23 study plots from 2011-2013, we found 1,644 nests (45 Clapper Rail, 142 Willet, 80 Nelson’s Sparrow, 349 Seaside Sparrow, 1,022 Saltmarsh Sparrow, and 6 American Black Duck). Mean daily nest success probabilities ($\pm$ SE) were as follows: Clapper Rail = 0.99 ± 0.01 ; Willet = 0.94 ± 0.01 ; Nelson’s Sparrow = 0.93 ± 0.01 ; Seaside Sparrow = 0.93 ± 0.01 ; Saltmarsh Sparrow = 0.93 ± 0.01 . Among the three sparrow species, where reneesting is common, we estimated seasonal fecundity. For Nelson’s Sparrows, fecundity was highest at the New Hampshire sites (mean $\pm$ 95% CI = 3.34 ± 0.34 offspring per female per season), which are farther upriver than the Maine sites (1.55 ± 0.39 offspring per female per season) and may experience less flooding as a result. For Seaside Sparrows, fecundity was highest in New Jersey (2.18 ± 0.33 offspring per female per season) and declined to the north. Saltmarsh Sparrow fecundity was highest in New Hampshire (1.89 ± 0.25 offspring per female per season), although fecundity was highly variable across sites and years and is likely driven by local processes. While nest success was similar (but variable) across the Saltmarsh Sparrow breeding range, nests were more likely to fail by predation in the south and flooding represented a larger proportion of failure in the north. In Connecticut, where historical nesting studies have been conducted over the last decade, nesting densities are declining for Saltmarsh Sparrow, Seaside Sparrow, and Clapper Rail, with Saltmarsh Sparrows showing the strongest decline.

Adult Songbird Survival – We conducted standardized mist-netting of tidal marsh specialist songbirds at 21 of our 23 reproductive plots in major marsh complexes from New Jersey to Maine from 2011 – 2014. Mark-recapture data from systematic surveys were augmented by targeted mist-netting of adult birds at nests at all study sites and by mist-netting birds during spring and fall migration at our Connecticut sites. We estimated apparent annual survival of adults using the complete-data likelihood of Cormack-Jolly-Seber (CJS) models. Female Saltmarsh Sparrow survival at an average site was 0.46 (credible interval: 0.41, 0.51); male survival was 0.49 (0.44, 0.55). Apparent survival for female (0.47; 0.37, 0.59) and male (0.43; 0.26, 0.59) Nelson’s Sparrows were not different from the equivalent rates for Saltmarsh Sparrows. Apparent survival of Seaside Sparrows was 0.52 (0.37, 0.71) for females and 0.57 (0.44, 0.75) for males. Survival rates for all three species were similar across sites and showed no clear evidence of latitudinal or other geographic patterns.

Population Viability – For Saltmarsh, Seaside, and Nelson’s sparrows, we created individual-based population models that propagate uncertainty from both parameter estimation and demographic stochasticity. We estimate that, based on vital rates over the course of this study, mean growth rates for Saltmarsh Sparrows over the next five years will be negative at all of our demographic plots. Assuming that our demographic plots are representative of the species range, 5% of marshes at most will have positive growth over the next 50 years. Global extinction risk for Saltmarsh Sparrow over the next 50 years is less than 5%, although the global population is expected to decline by 92% (95% confidence interval: 7 – 100%) during this period,

putting the species on a clear trajectory towards extinction. If individual states are to ensure a 50% chance of avoiding Saltmarsh Sparrow extirpation over the next 50 years, then they will need to ensure a population that includes at least 7,500 females. Of the states for which we have demographic data, only New Jersey currently has a population this large, and most states will need to work with neighboring states to support ensure viable populations.

Our estimates suggest that Maine's Nelson's Sparrow population is likely not viable in the long-term without immigration from other regions (80% chance of extinction within 50 years). For New Hampshire, extinction risk is less than 50% if the starting female population size is at least 100 individuals. This higher persistence probability for New Hampshire arises because of higher estimated fecundity than in Maine (although we measured reproduction at only two sites in New Hampshire and six in Maine).

We found minimal risk of extinction over the next 50 years for Seaside Sparrows south of Connecticut, but we estimate that there is an approximately 50% chance of being extirpated from Connecticut over the next 50 years. Although Seaside Sparrows are rare in states farther north (thus prohibiting explicit PVA), it is likely that their small populations would also go extinct. In order to reduce the extinction risk in Connecticut to less than 50%, the starting population size would need to be increased to 5,000 females, considerably higher than our current estimated population in southern New England. For New York and New Jersey, extinction risk is less than 25% if the female population size remains above 100 individuals.

Decision Support Tools for Conservation – We compared different methods of conservation planning in two states (Delaware and Connecticut). In Delaware we 1) determined the tidal marsh areas in Delaware that support the greatest density of breeding tidal marsh obligate birds, 2) identified the extent of protected and unprotected saltmarsh habitat in a focal area of the state, 3) identified and compared benefit-targeting and optimization-selected parcel portfolios that maximize bird density on unprotected marsh habitat in three budget scenarios, and 4) determined the effect of three sea level rise scenarios on the proportion of land cover types within the optimized parcels. The optimization method selected more parcels, protected more marsh area, and conserved more tidal marsh obligate birds, than the more traditional benefit targeting method. When benefit targeting and optimization protected the same number of birds, optimization provided a cost savings of \$1.75M-\$2.9M. Given the increasing rates of inundation from sea level rise, the potential future benefits of adjacent agricultural lands to tidal marsh birds through marsh migration should be incorporated into optimization models for more effective conservation planning and spending of limited financial resources.

In Connecticut a meeting of most of the major organizations involved with bird conservation together developed a set of prototype Decision Support Tools (DST) based on a systematic planning process (Margules and Pressey 2000). Because land prices in Connecticut are high, a successful implementation strategy will hinge on achieving efficiency in decision-making that will give the greatest conservation benefit per dollar spent. A challenge to achieving this efficiency is that land prices change with markets over time, and are not predictable with complete certainty. Therefore, the DST we developed explicitly accounts for the uncertainty of how much it will cost to protect land, providing practitioners with the decision-making framework to make low-risk, high-efficiency decisions. The approach we have developed is purposefully very flexible, easy to calculate and understand, and based on the latest research in

conservation biology and decision theory. We have deliberately applied the approach to a simple example with a small set of conservation targets and a single conservation action in order to illustrate the method as a “proof-of-concept”. The approach can easily be expanded or applied to other systems by including a larger set of targets and considering a wider range of conservation actions (e.g., restoration), or even explicitly trading-off the costs and benefits of alternative conservation actions. Expanding this DST to address these issues statewide is the focus of an ongoing follow-up study.

Conclusions – Systematic and standardized study of tidal marshes across the northeastern United States indicates that states will need to work together to ensure the viability of tidal marsh bird populations into the future. While states south of New York possess the most extensive marshes and the largest concentrations of SGCN, New York and New England also possess significant portions of tidal marsh taxa, particularly the imperiled Saltmarsh Sparrow. Tidal marsh specialists are declining across the region, and Saltmarsh Sparrows in particular show multiple, independent pieces of evidence for severe decline and elevated extinction risk. Marsh alteration in the form of tidal restriction is strongly correlated with decline and restoring and augmenting sediment transport should be a high priority for maintaining local marshes and the bird populations they support. Rates of reproduction and survival for tidal marsh taxa appear highly variable across the Northeast, suggesting that local processes drive viability and that local actions may successfully lower extirpation risk. We present two approaches to implement conservation actions systematically and efficiently using this scientific information and suggest that further experimentation in engaging stakeholders is necessary to guide local actions. What is clearest is that coordination is necessary over regional scales to maintain tidal marsh bird populations into the next century.

II. Introduction

Tidal marshes are ecotonal ecosystems and form the dominant transition zone between terrestrial and marine communities in eastern North America (Reinold 1977; Mitsch and Gosselink 1993). This pattern is not reflected on other continents, and the total area of tidal marsh worldwide is estimated to be less than 45,000 km², with over one-third of these marshes found along the US Atlantic and Gulf coasts (Greenberg 2006; Greenberg et al. 2006).

The tidal marshes of eastern North America also possess higher levels of vertebrate biodiversity and endemism than the tidal marshes of any other region worldwide, with 83 breeding vertebrate species, 22% of which occur only in tidal marshes or possess subspecies found only in tidal marshes (Greenberg and Maldonado 2006). Eastern North American tidal marshes are home to 56% of the endemic saltmarsh species or subspecies in the world. North America, therefore, plays a critical role in the conservation of the ecosystem's global flora and fauna. Tidal marsh as an ecosystem is to a large extent a North American resource, and therefore, its conservation is primarily a North American responsibility.

Tidal marshes also perform many key services to humans (Barbier et al. 2011). They absorb the energy of ocean storms, which helps to preserve shorelines (Daiber 1986), improve water quality in bays and estuaries (Heinle and Flemer 1976; Valiela and Teal 1979; Dame et al. 1992; Valiela et al. 2000; Koch and Gobler 2009), provide nutrients to marine food webs (Odum 1969), and supply critical habitat for both the reproduction of many ocean species (Boesch and Turner 1984) and for non-breeding use by an entire community of migratory birds appreciated by birders and sportsmen alike (Master 1992, Erwin 1996, Brown et al. 2002).

Because of their restricted, linear distribution along the shoreline, tidal marshes compete for space with humans more than many other habitats. More than half the people in the USA (Alaska excluded) live in coastal counties, even though these counties constitute only ~17% of the land; in the Northeastern USA, 77% of people live in coastal counties (Crossett et al. 2004). Such development has contributed to the loss of approximately half of US coastal wetlands (Tiner 1984; Dahl 1990). These losses are exacerbated by the small area that tidal marshes occupied prior to modern human development and are linked to the marshes' ability to support endemic species at state and regional scales (Benoit and Askins 2002; Greenberg and Maldonado 2006).

As an ecotonal system, the health and integrity of the tidal marsh are driven by both terrestrial and marine inputs. This leaves the ecosystem open not only to outright loss, but also to the severe degradation of remaining habitat. Along the highly developed US coastlines, tidal marshes are found at the mouths of some of the country's most human-impacted drainages (e.g. the Susquehanna, Delaware, Hudson, and Connecticut Rivers) and along the shipping routes of some of the busiest ports (e.g. Norfolk, Baltimore, and New York). This overlap with human use has contributed to a suite of impacts that have degraded ecosystem quality, including nitrification (Bertness et al. 2002), contamination by heavy metals (Shriver et al. 2006), spread of invasive plants (Benoit and Askins 1999), increases in nest predators (Greenberg 2006), widespread ditching and other hydrologic alterations for insect management (Daiber 1986; Erwin et al. 1994; Wolfe 1996), and increases in salinity due to the retention of river flows for human use (Sipple 1971). There are no pristine tidal marshes left in the region. By the late 20th century, 90% of northeastern salt marshes had been ditched to some degree (Daiber 1986); 50-75% of the salt marsh in the Chesapeake and Delaware Bays were functionally lost (Stevenson et al.

2002); and the entire Massachusetts Bay estuary system had poor sediment toxicity (Massachusetts Executive Office of Environmental Affairs 1992).

The coastal placement of tidal marshes is responsible for another large and emerging threat to the ecosystem's persistence, sea-level rise. Over the last century, average global sea level has risen by ~1.5 mm/year (IPCC 2013). Since 1993, satellite and tide gauge estimates suggest a higher rate of ~3.2 mm/yr, and accelerated increases are projected for the future. Even under optimistic scenarios, half a meter of sea-level rise is expected by the end of this century (Schaeffer et al. 2012, IPCC 2013). Locally, rates of sea-level rise vary considerably. For example, along the US Atlantic Coast, rates of sea-level rise from Cape Hatteras to Boston are accelerating faster than the global average (Sallenger et al. 2012), and it has been suggested that anomalously large short-term increases in sea level, such as occurred in the northeastern US during 2009-10, might become more frequent (Goddard et al. 2015). Relative sea-level rise has been linked to altered vegetation in marshes in the northeast (Warren and Niering 1993) and caused interior marsh loss across the seaboard: Four of five well-monitored *Spartina* marshes of high conservation value from Virginia to New England have lost 10-20% of their area due to salt-water intrusion in the last 50 years (0.2-0.7% per year: Erwin et al. 2004). Projected acceleration of sea-level rise is expected to result in annual tidal marsh losses of 0.5-1.5% (Greenberg 2006).

Climate change also may impact the unique bird assemblage of the tidal marsh by increasing the frequency (Resio and Hayden 1975; Hayden 1981) and intensity (Emanuel 1987; Knutson 1998; Bacon and Carter 1991) of storm surges. Flooding can be a strong determinant of bird reproduction in the tidal marsh (Gjerdrum et al. 2005, 2008a; Greenberg et al. 2006, Bayard and Elphick 2011), and both sea-level rise and storm surge increases are likely to raise this threat for many marsh specialists, most of which are near-ground nesters. The combination of habitat loss and reduced vital rates, suggests that small sea-level increases could push populations to a threshold beyond which rapid declines are likely. For example, early efforts to model the effect of such losses on Seaside Sparrows in Connecticut suggested that even moderate sea-level rise (0.5 m) could make persistence unlikely (Shriver and Gibbs 2004).

Preventing species from entering an "extinction vortex" (Gilpin and Soulé 1986) that would warrant listing under the US Endangered Species Act requires that we quantify species vulnerability, identify the thresholds for serious declines and the time frame on which they will be reached, and investigate potential solutions that would preempt the need for drastic, and costly, remedies. Many organizations recognize the threats to birds that use northeastern USA tidal marshes. Saltmarsh Sparrow *Ammodramus caudacutus* is listed as globally Vulnerable by the International Union for Conservation of Nature (BirdLife International 2015), and both King, *Rallus elegans*, and Black Rail, *Laterallus jamaicensis*, are listed as Near Threatened; thirteen species on the North American Bird Conservation Initiative's (NABCI) Watch List regularly use tidal marshes (Rosenberg et al. 2014); and 26 bird species that use these habitats during summer are listed as SGCN by states in USFWS Region 5 (Table 1).

This project focuses on the coastal zone from Virginia to Maine, encompassing habitat in ten states. Each state has identified tidal marshes as key habitat for SGCN species in their State Wildlife Action Plans (SWAPs). Subsequently, states have identified priority actions in their SWAPs to address conservation needs. Ranging from simple inventories to detailed demographic evaluations, northeast coastal states have independently identified conservation needs in tidal marshes as a priority and have outlined explicit actions to address them. In this report we detail work conducted to address many of these needs.

Table 1. Species of Greatest Conservation Need (SGCN) in USFWS Region 5 that we set out to measure in this study. Focal species for which we collected reproductive and survey data are in boldface text; those for which only survey data were gathered are in plain text; and those that we surveyed using playback of recorded vocalizations are underlined. Also noted is (a) whether a species was considered Threatened (T), Endangered (E), or of Special Concern (SC) within each state at the start of the project, (b) which states considered a species to be an SGCN at the start of the project, and (c) whether a species is currently on the International Union for Conservation of Nature Red List (“IUCN”) or North American Bird Conservation Initiative Watch List (“NABCI”).

Species	Listed as T/E/SC	Listed as SGCN	International Listing
Least Bittern	ME, NH, MA, RI, CT, NY, NJ, MD	ME, NH, MA, RI, CT, NY, NJ, DE, MD, VA	
Great Blue Heron	RI, NJ	ME, NH, RI, CT, NJ, DE, MD	
Great Egret	RI, CT, VA	ME, RI, CT, NY, NJ, DE, MD, VA	
Snowy Egret	RI, CT, NJ	ME, MA, RI, CT, NY, NJ, DE, MD	
Tricolored Heron	NJ, VA	ME, NY, NJ, DE, MD, VA	
Little Blue Heron	CT, NJ	ME, RI, CT, NY, NJ, DE, MD, VA	
Black-crowned Night-Heron	ME, RI, NJ, DE	ME, MA, RI, CT, NY, NJ, DE, MD, VA	
Yellow-crowned Night-Heron	RI, CT, NJ, DE, VA	RI, CT, NY, NJ, DE, MD, VA	
Glossy Ibis	RI, CT, VA	ME, RI, CT, NY, NJ, DE, MD, VA	
American Black Duck		ME, NH, MA, RI, CT, NY, NJ, DE, MD, VA	
Clapper Rail	RI	RI, CT, NJ, VA	
<u>Virginia Rail</u>		ME, CT, NJ, VA	
<u>Black Rail</u>	CT, NY, NJ, DE, MD, VA	CT, NY, NJ, DE, MD, VA	IUCN, NABCI
Black-necked Stilt		DE	
Willet	NH, RI	ME, NH, RI, NY, NJ, DE, MD	NABCI
Laughing Gull	ME	ME, MA, NY, MD	
Common Tern	ME, NH, MA, CT, NY, NJ, DE	ME, NH, MA, RI, CT, NY, NJ, DE, MD, VA	
Forster's Tern	DE, VA	NY, NJ, DE, MD, VA	
Willow Flycatcher		ME, RI, CT, NY, NJ, DE, MD, VA	
Sedge Wren	ME, NH, MA, CT, NY, NJ, DE, MD, VA	ME, NH, MA, CT, NY, NJ, DE, MD, VA	
Marsh Wren		ME, RI, CT, NJ, DE, MD, VA	
Common Yellowthroat		ME, RI	
Nelson's Sparrow	ME, NH	ME, NH	
Saltmarsh Sparrow	ME, NH, CT, VA	ME, NH, MA, RI, CT, NY, NJ, DE, MD, VA	IUCN, NABCI
Seaside Sparrow	NH, RI, CT, NY	NH, MA, RI, CT, NY, NJ, DE, MD, VA	
Coastal Plain Swamp Sparrow	MD	MD	

III. Project Objectives

To identify critical areas for tidal marsh bird conservation and identify which marshes and species in the Northeast/Mid-Atlantic are most sensitive to land and seascape change, we had the following objectives.

Objective 1: To estimate the distribution and relative geographic abundance of bird species breeding in the tidal high marsh from Maine to Virginia using a combination of passive and broadcast surveys. Our protocol and sampling framework focused on the distribution and abundance of five diurnal species that nest primarily in the high marsh zone:

- a. Saltmarsh Sparrow, *Ammodramus caudacutus* (formerly Saltmarsh Sharp-tailed Sparrow)
- b. Nelson's Sparrow, *Ammodramus nelsoni* (formerly Nelson's Sharp-tailed Sparrow)
- c. Seaside Sparrow, *Ammodramus maritimus*
- d. Willet, *Tringa semipalmata*
- e. Clapper Rail, *Rallus crepitans*

We also surveyed for tidal marsh species that breed in low abundance in this region, although our diurnal, point-count approach may underestimate local populations. The species in this group are of high conservation concern across their entire range. Although our local estimates may be biased low, our data will help to assess the relative importance of breeding areas within the coastal portion of US Fish and Wildlife Service (USFWS) Region 5, information that is crucial for their long-term conservation. These species are:

- f. Black Rail, *Laterallus jamaicensis*
- g. American Black Duck, *Anas rubripes*

For a third group of species that breed only in the upland fringe of the high marsh or that, in USFWS Region 5, use marsh primarily for foraging, we provide regional information on the degree of tidal marsh use. This information is critical to understanding how tidal marsh loss and degradation may impact species with more general habitat associations. These species are:

- h. Wading birds (Least Bittern, *Ixobrychus exilis*; Great Egret, *Ardea alba*; Snowy Egret, *Egretta thula*; Little Blue Heron, *Egretta caerulea*; Great Blue Heron, *Ardea herodias*; Tricolored Heron, *Egretta tricolor*; Black-crowned Night-Heron, *Nycticorax nycticorax*; Yellow-crowned Night Heron, *Nyctanassa violacea*; Glossy Ibis, *Plegadis falcinellus*)
- i. Virginia Rail, *Rallus limicola*
- j. Black-necked Stilt, *Himantopus mexicanus*
- k. Laughing Gull, *Leucophaeus atricilla*
- l. Common (*Sterna hirundo*) and Forster's (*Sterna forsteri*) Terns
- m. Marsh fringe songbirds (Willow Flycatcher, *Empidonax traillii*; Marsh Wren, *Cistothorus palustris*; Sedge Wren, *Cistothorus platensis*; Yellow Warbler, *Setophaga petechia*; Common Yellowthroat, *Geothlypis trichas*; Coastal Plain Swamp Sparrow, *Melospiza georgiana nigrescens*; Red-winged Blackbird, *Agelaius phoeniceus*)

Objective 2: To compile information on hydrologic and other manipulations, as available, to examine the current bird community in light of past management.

Objective 3: To conduct thorough nest-searches to estimate the high marsh nest abundance, density, and productivity for species $a - f$ at three intensive study sites (in Maine, Connecticut and New Jersey), chosen to represent the breadth of conditions across USFWS Region 5. Note that multiple “demographic” plots were studied at each site, and that additional sites were added through collaborations with colleagues such that we ultimately collected reproductive data from 23 demographic plots spread across seven states.

Objective 4: To estimate adult survival rates for and Nelson’s sparrows at our northern demographic (Maine sites) and for and Seaside sparrows at our southern (Connecticut and New Jersey) demographic sites. Note that, through collaborations with colleagues, we ultimately collected survival data from 21 demographic plots spread across seven states.

Objective 5: To parameterize a species-specific, Markov-Chain, seasonal fecundity model (Program MC-Nest, Bennett and Etterson 2007) using results from Objectives 3 & 4 and additional published latitudinal trends in tidal flooding risk, clutch size, and breeding season length. This model will be used to predict latitudinal variation in potential local population growth for species of tidal marsh sparrow.

Objective 6: To use data from Objectives 1, 3, 4, & 5 to model geographic trends in density (all species), nest density/productivity (species $a - g$), and adult survival (species $a - c$) to determine where within USFWS Region 5 the greatest responsibility lies for conserving each species.

Objective 7: To conduct population viability analysis (PVA) at state and regional scales for all three focal species for which we gathered detailed demographic data in order to model the sensitivity of these species to state-scale landscape changes caused by sea-level rise.

Objective 8: To estimate change in relative abundance since the 1990s of all surveyed species for which adequate data exist.

Objective 9: To estimate change in nesting density and productivity over the last decade for sites with historical reproductive data.

Objective 10: To facilitate the transfer and use of research information for on-the-ground implementation by establishing a working group of local, state, federal, and NGO stakeholders within Connecticut to develop Decision Support Tools that address the conservation issues identified by this project. Note that we also conducted a second pilot in Delaware, testing different approaches in the two states and have used the results and feedback on these pilots to develop a unified approach that can be used across the entire region.

IV. Distribution & Abundance

Methods

Study Area

We conducted this research in tidal marsh habitat from Maine to Virginia during the 2011-12 breeding seasons (April-July; Fig. 1). Coastal marshes from the Canada-Maine border to Cape Cod, Massachusetts on the Gulf of Maine are classified as Acadian coastal salt marsh (NatureServe ID: CES201.578; Comer et al. 2003, Ferree and Anderson 2013). These polyhaline marshes are interspersed throughout the rocky sections of the Gulf of Maine coast along the ocean shoreline and estuary mouths. Acadian coastal salt marsh is dominated by graminoids *Spartina patens* and *S. alterniflora*, and includes patches of other

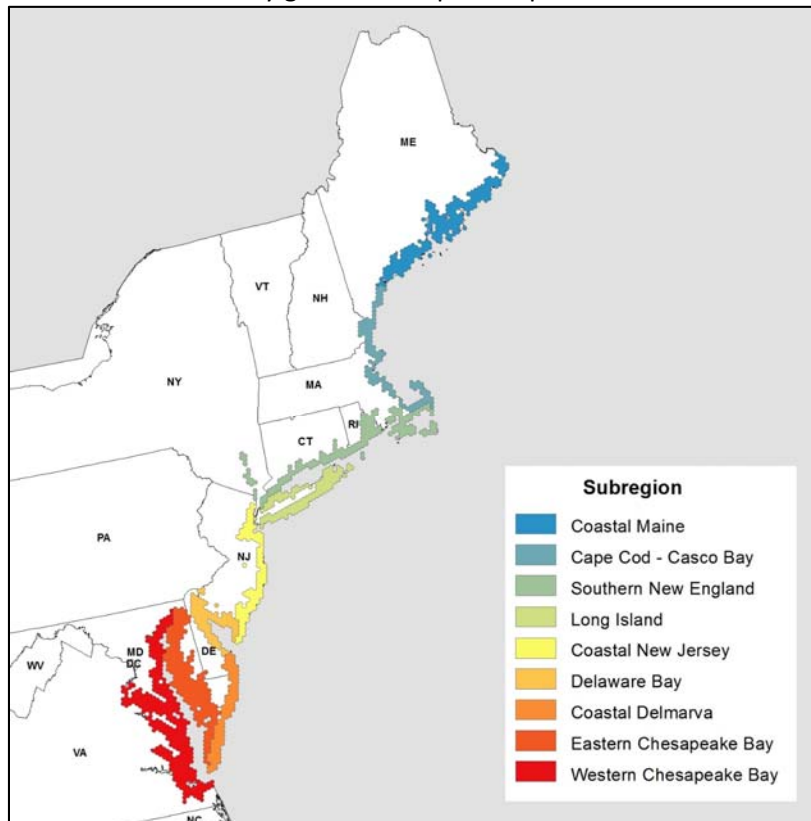


Figure 1 The sampling universe for surveys of tidal marsh birds in the Northeast USA delineated into subregions.

graminoids (e.g., *Juncus balticus*, *J. gerardii*, and *Puccinellia maritima*) and forbs (e.g., *Limonium carolinianum* and *Plantago maritima* var. *juncooides*). Acadian coastal salt marshes typically occur as small patches, but may be more extensive where topography allows, although rarely as extensive as tidal marshes elsewhere along the USA Atlantic coast (Comer et al. 2003, Ferree and Anderson 2013). Northern Atlantic Coastal Plain tidal salt marsh extends from Cape Cod, Massachusetts, to the mouth of the Chesapeake Bay, and intermittently along the southern coast of the Gulf of Maine to southern Maine (NatureServe ID: CES203.519; Comer et al. 2003, Ferree and Anderson 2013). This intertidal system occurs on the

bayside of barrier beaches and along the outer mouths of tidal rivers where saline to mesohaline conditions are not strongly impacted by freshwater flow. Northern Atlantic Coastal Plain tidal salt marshes also are dominated by graminoids *S. patens* and *S. alterniflora*, but tend to have more *Distichlis spicata* and *Salicornia* spp. than Acadian coastal salt marsh, as well as more developed upland borders containing shrubs such as *Iva frutescens*, *Baccharis halimifolia*, and *Juniperus virginiana* with an herbaceous layer of *Panicum virgatum*. Average patch size of Acadian coastal salt marsh is 2 ha and the largest single patch is 337 ha, compared to 4 ha and 7,877 ha, respectively, for Northern Atlantic Coastal Plain tidal salt marsh.

Sampling Design

Our sampling design followed the sample selection protocol recommendations developed by Johnson et al. (2009) to monitor secretive marsh birds at regional and continental scales. We used a two-stage cluster sampling design (Thompson 2012) with generalized random-tessellation stratified (GRTS) sampling at each stage (Stevens and Olsen 1999, 2003, 2004) to distribute survey points. The GRTS survey design emphasizes a spatially balanced sample distribution; a sample is dispersed such that the spatial density pattern of the sample closely mimics the spatial density pattern of the environmental resource (Stevens and Olsen 1999, 2003, 2004). The two-stage cluster design required a geographical division of the study area and separate selection protocols for the two types of sampling units: primary sampling units (PSUs; hexagons) and secondary sampling units (SSUs; survey points). We used a North American continental hexagon grid (40 km² hexagons) to generate the PSU sampling universe (www.tidalmarshbirds.org). We selected the subset of the continental grid that included all hexagons located in the 10 Northeast U.S. coastal states that contained Estuarine Intertidal Emergent Wetland (code 'E2EM'; Cowardin et al. 1979) as designated by state wetland geospatial data from the National Wetlands Inventory (NWI; Wilen and Bates 1995, U.S. Fish and Wildlife Service – National Wetlands Inventory 2010). We compiled and processed the Estuarine Intertidal Emergent Wetland geospatial features in ArcGIS ver. 9.3 (ESRI 2009) to develop a single spatial layer of salt marsh in the Northeast. Northeast hexagons that contained salt marsh became the sampling universe for the selection of PSUs (Fig. 1, Table 2). We did not divide the sampling universe further by wetland size (small and discrete or large and extensive) or by accessibility, as proposed by Johnson et al. (2009), because the NWI layer we used for the entire region digitizes very small polygons of tidal marsh that are effectively part of the same larger marsh, and because we could not determine wetland accessibility prior to sampling.

We used the 'spsurvey' package (Kincaid and Olsen 2012) in the R statistical program (R Core Team 2014) to select hexagons and survey points. We used three sampling strata to select hexagons: subregion, state lands, and federal lands (USFWS and National Park Service [NPS]). Subregion boundaries were based on Conway and Droege (2006) and generally delineated by major geomorphological features (e.g., Long Island, Delmarva Peninsula, Chesapeake Bay; Fig. 1, Table 2). We randomly selected 25 hexagons as the core sample and 10 hexagons as oversample for the initial hexagon selection within each subregion (GRTS selection). We selected oversample hexagons in the event core sample hexagons could not be sampled owing to saltmarsh inaccessibility (e.g., denied access, impassible terrain) or absence. Next, we randomly selected 25 hexagons that contained tidal marsh on state lands in each subregion. Finally, we selected all hexagons that contained tidal marsh on USFWS and NPS lands, because the two agencies conduct wildlife surveys and are likely to continue to do so into the future. Our prioritization of hexagons with protected tidal marsh did not preclude sampling private tidal marsh within the hexagons, but simply ensured that sampling would be permitted at a reasonable number of sites across the study area. We used spatial data from the Protected Areas Database (U.S. Geological Survey, Gap Analysis Program 2011) to determine the hexagons that contained protected tidal marsh. We combined the federal lands hexagons with the GRTS-selected hexagons (i.e., core and state hexagons) to create the sampling frame. We excluded hexagons that contained less than 10 ha of marsh, although there was no lower limit on individual marsh size; hexagons with less marsh can support fewer sampling points, potentially requiring excessive travel time for few sampling locations.

Table 2. Subregions used for sampling stratification for surveys of tidal marsh birds, and summary statistics describing the sampling universe (number of hexagons and marsh area [ha]) and sampled area (number of hexagons, marsh area [ha], and number of survey points). Subregion boundaries were developed based on suggestions by Conway and Droege (2006; also see Fig. 1 for subregion map and state abbreviation definitions). NA, not applicable.

Subregion	State(s)	Boundaries	Sampling universe		Sampled area		Survey points
			Hexagons	Marsh area	Hexagons	Marsh area	
Coastal Maine	ME	Lubec, ME to north side Casco Bay, ME	208	6,223	43	2,573	244
Cape Cod - Casco Bay	ME/NH/MA	Casco Bay, ME to Cape Cod, MA (incl. north side U.S. Rt. 6)	113	20,472	44	10,826	340
Southern New England	MA/RI/CT/NY	South of Cape Cod, MA (incl. south side U.S. Rt. 6) to Hudson River, NY	180	10,127	35	4,005	205
Long Island	NY	Long Island, NY	107	9,920	31	6,263	119
Coastal New Jersey	NY/NJ	Staten Island, NY; NJ Meadowlands to Cape May, NJ (oceanside)	109	50,354	43	32,977	293
Delaware Bay	NJ/DE	Cape May, NJ (bayside) to Lewes, DE (bayside)	88	59,956	23	24,444	153
Coastal Delmarva	DE/MD/VA	Lewes, DE (oceanside) to Fisherman Island National Wildlife Refuge, VA	93	45,333	36	25,683	241
Eastern Chesapeake Bay	MD/VA	Chesapeake Bay coast east of Susquehanna River mouth	212	78,337	22	28,272	185
Western Chesapeake Bay ¹	MD/VA	Chesapeake Bay coast west of Susquehanna River mouth	311	35,409	NA	NA	NA

¹ Western Chesapeake Bay was included in the sampling universe, but not in the comprehensive survey.

We used 'spsurvey' to randomly locate 10 survey points and 10 oversample survey points in marsh in each hexagon. To improve our ability to make comparisons with previous tidal marsh surveys, we also acquired coordinates of existing tidal marsh bird survey points from historical and ongoing marsh bird surveys (20 projects total; Table 3). We used ArcGIS to combine existing point locations with the randomly generated points, only retaining random points 400 m or more from established points. Point spacing followed the Standardized North American Marsh Bird Monitoring Protocol's recommendation of a minimum distance of 400 m between survey points (Conway 2011). Once the previously established and new, randomly selected points were identified, we ground-truthed all sampling points, prioritizing established points that had historical survey data. We ground-truthed the established points first (if the hexagon possessed them) and then the randomly located survey points followed by the oversample points until we had identified up to 10 survey points in accessible, appropriate saltmarsh habitat in each selected hexagon. Survey points consisted of a mix of wetland edge and marsh interior locations, and were accessed by foot, vehicle, and non-motorized or motorized boats.

Defining Saltmarsh Patches

We delineated habitat patches to assess species abundance within discrete, biologically relevant spatial areas and to allow for comparisons in abundance patterns across the landscape. We used the Estuarine Intertidal Emergent Wetland spatial layer developed in the survey sampling design to define saltmarsh habitat patches. We used ArcGIS ver. 9.3 (ESRI 2014) to create a 50 m buffer around the polygon features. Polygons with buffers that intersected were considered the same patch based on home range size and movement estimates for Nelson's and Saltmarsh sparrows (Shriver et al. 2010). For each defined patch we recorded the state (e.g., Maine, New Hampshire), subregion (e.g., Coastal Maine, Cape Cod to Casco Bay), longitude, latitude, and area.

Bird Sampling

We used the North American Marsh Bird Monitoring Protocol (Conway 2011) to estimate the distribution and abundance of tidal marsh birds within our study region. At all survey points during the 2011-12 breeding seasons, we conducted 5-minute passive point-counts divided into 1-minute intervals followed immediately by a sequence of 30-second marsh bird broadcasts couple with 30-seconds of silence (Conway 2011). We selected call-broadcast species based on the species thought to breed in marshes in each subregion and from additional recommendations by federal and state wildlife biologists. A single observer conducted surveys in the morning from 30 minutes before sunrise to approximately 1100 hours and visited each sampling point 2 - 3 times from April 15 to July 31. We did not survey during high winds, sustained rain, or heavy fog. During each survey we estimated the number of individuals for each species detected in three distance categories: 0–50 m, 50–100 m, and >100 m. To standardize the sampling procedure across the entire region, we used detections of marsh birds from the five-minute passive period for all following analyses. We limited analyses to records from the 0–50 m distance band to reduce measurement error in the count data (e.g., difficulty estimating far distances from auditory cues and species misidentification as distance from the observer increases; Simons et al. 2009) and to keep analysis methods consistent across species.

Table 3. Historical and ongoing studies with existing marsh bird survey points; studies are listed by organization type, then from north to south.

Organization	Historical study	State(s) surveyed	Resurveyed ¹
Academic	University of Connecticut	CT	Y
	State University of New York, College of Environmental Science and Forestry	NH, MA, RI, CT	Y
State Government	Maine Department of Inland Fisheries and Wildlife	ME	Y
	New Jersey Division of Fish and Wildlife (Rail surveys)	NJ	Y
	New Jersey Division of Fish and Wildlife (Saltmarsh birds)	NJ	Y
	Delaware Department of Natural Resources and Environmental Control	DE	Y
	Maryland Department of Natural Resources	MD	Y
Federal Government	U.S. Fish and Wildlife Service (Salt marsh integrity project pilot study)	ME, MA, RI, CT, NY, NJ, DE, VA	Y
	Rachel Carson National Wildlife Refuge	ME	Y
	Parker River National Wildlife Refuge	MA	Y
	Monomoy National Wildlife Refuge	MA	Y
	Bombay Hook National Wildlife Refuge	DE	Y
	Smithsonian Environmental Research Center	VA	N
	Smithsonian Migratory Bird Center	DE	Y
Non-Governmental	New Hampshire Audubon (Hampton)	NH	Y
	Massachusetts Audubon	MA	Y
	New Jersey Audubon (Gateway)	NJ	Y
	New Jersey Audubon (Raritan)	NJ	N
	New Jersey Audubon (Meadow)	NJ	Y
	New Jersey Audubon (Peters)	NJ	Y

¹ 'Y' indicates that we resurveyed historical points in 2011 and/or 2012, and an 'N' indicates that no points were resurveyed.

Estimating Distribution and Abundance

We estimated the distribution based on the percent of survey points where a given species was detected on at least one visit. We estimated species abundance within each surveyed patch using the 'multinomPois' function (Royle 2004) in the 'unmarked' package (Fiske and Chandler 2011) in the R statistical program (R Core Team 2014). We used the time-of-detection method to account for species detection probability as a function of survey visit to control for seasonal differences in detection rates (Farnsworth et al. 2002). We took two approaches for estimating state and regional population totals (see below). For SGCN species (Table 1), we used the abundance estimates within surveyed patches and estimated a total based on the density of the species and the amount of marsh habitat in the state or region. For focal species (Clapper Rail, Willet, Nelson's, , and Seaside sparrows), we used a Bayesian network (BN) modeling framework (Koller and Friedman, 2009) to predict the probability of species presence and density in marsh habitat patches. We used the regional sampling effort to: (1) predict focal species distribution and abundance and (2) estimate population sizes at state and subregional scales. We used our occurrence and density estimates for sampled patches (Wiest et al. in press) to develop BNs for each focal species independently and used the same model development, performance, and validation approaches to be consistent across species. The resulting models provide spatially explicit, geographical predictions of species distribution and abundance that can be used for population monitoring and tidal marsh bird conservation planning.

Bayes Net Model Covariates

Saltmarsh Patches - We defined saltmarsh habitat patches to model focal species distribution and abundance (Wiest 2015). We recorded 22 covariates at four spatial scales for each patch in five categories: location and dimension, land use and land cover, geomorphic setting, sea level trend, and human disturbance (Table 4). We chose patch features that are known to influence focal species distribution and abundance and can be obtained from remote-sensing data for the entire Northeast. We used ArcGIS ver. 9.3 (ESRI, 2014) for all geospatial calculations unless stated otherwise. We recorded patch-location covariates: state (e.g., Massachusetts, Rhode Island), subregion (e.g., Cape Cod to Casco Bay, Southern New England), centroid coordinates (longitude and latitude), and patch area and perimeter length during patch development (Wiest et al. in press).

Land use and land cover - We calculated the proportion of high marsh in a patch using a raster file developed by Correll et al. (unpublished data). The raster quantified high marsh areas in the Northeast using Landsat Thematic Mapper imagery and local tidal covariates. High marsh was defined as an area dominated by saltmeadow cordgrass (*Spartina patens*), smooth cordgrass-short form (*S. alterniflora*), black grass (*Juncus gerardii*), and/or saltgrass (*Distichlis spicata*). We calculated the proportion of five land use and land cover categories (i.e., natural lands, agriculture, developed, open water, and marsh) within 150-m and 1,000-m buffers around each patch using The Nature Conservancy spatial data (Ferree and Anderson, 2013). We considered any land cover type not classified as agriculture, developed lands, or open water, as natural lands. We used a subset of the natural land cover types to calculate the proportion of marsh as an index of habitat connectivity (Winfree et al., 2005). We considered the following five categories as marsh: (1) Acadian estuary marsh; (2) Acadian coastal salt marsh; (3) North Atlantic coastal plain tidal salt marsh: salt/brackish/oligohaline; (4) North Atlantic coastal plain brackish/fresh & oligohaline tidal marsh; and (5) Atlantic coastal plain embayed region tidal freshwater/brackish marsh (Comer et al., 2003; Ferree and Anderson, 2013).

Table 4. Patch covariates, grouped by geographic context, included in Bayesian network models and covariate bin categories developed to predict the occurrence and density of tidal-marsh-specialist birds in Northeast USA. The shaded boxes indicate which covariates were included in the models. Land cover land use covariates are proportions.

Geographic level Covariate	Model							Bin categories¹			
	All 1	Sub 2	All 2	Sub 3	All 3	Sub 4	All 4	1	2	3	4
Site											
Area (ha)								0.0-5.0	5.0-50.0	50.0-100.0	≥ 100
Perimeter (m)								137.0-700.0	700.0-2,500.0	2,500.0-15,000.0	≥ 15000
High marsh								0.0-0.01	0.01-0.15	0.15-0.50	0.50-1.0
Local											
Natural 150								0.0-0.25	0.25-0.50	0.50-1.0	NA ²
Agriculture 150								0.0-0.01	0.01-0.15	0.15-0.53	NA
Developed 150								0.0-0.10	0.10-0.25	0.25-0.99	NA
Open water 150								0.0-0.10	0.10-0.25	0.25-0.92	NA
Marsh 150								0.0-0.05	0.05-0.10	0.10-0.47	NA
Road density								0.0-20.0	20.0-50.0	50.0-230.0	NA
Landscape											
Natural 1000								0.0-0.25	0.25-0.50	0.50-1.0	NA
Agriculture 1000								0.0-0.01	0.01-0.15	0.15-0.61	NA
Developed 1000								0.0-0.10	0.10-0.25	0.25-0.91	NA
Open water 1000								0.0-0.10	0.10-0.25	0.25-0.93	NA
Marsh 1000								0.0-0.05	0.05-0.10	0.10-0.59	NA
Sea level trend (mm/yr)								1.70-2.0	2.0-2.63	2.63-5.48	NA

Table 4. Continued.

Geographic level Covariate	Model							Bin categories ¹			
	All 1	Sub 2	All 2	Sub 3	All 3	Sub 4	All 4	1	2	3	4
Regional											
State ³								Maine	New Hampshire	Massachusetts	Rhode Island
Subregion ⁴								Coastal Maine	Cape Cod - Casco Bay	Southern New England	Long Island
Longitude (°W)								-77.380 – -73.965	-73.965 – -71.855	-71.855 – -66.800	NA
Latitude (°N)								36.400 – 40.490	40.490 – 41.400	41.400 – 45.100	NA
Primary geomorphic setting ⁵								Back-barrier lagoon marsh	Estuarine brackish marsh	Estuarine embayment	Open coast
Secondary geomorphic setting								Back-barrier lagoon marsh	Estuarine brackish marsh	Estuarine embayment	None
Tertiary geomorphic setting								Tidal fresh marsh	None	NA	NA

¹ Bin categories do not overlap.

² NA = not applicable.

³ Bins are listed north to south. Additional bins: Connecticut, New York, New Jersey, Delaware, Maryland, and Virginia.

⁴ Bins are listed north to south. Additional bins: Coastal New Jersey, Delaware Bay, Coastal Delmarva, and Eastern Chesapeake Bay.

⁵ Additional bin: Tidal fresh marsh.

Geomorphic setting - We reviewed aerial photographs in ArcGIS ver. 10.2.2 (ESRI, 2014) to characterize patch geomorphic setting. The physical setting of Northeast tidal marshes varies along the coast and settings are characterized by differences in hydrodynamics, sediment sources, and plant community characteristics (Cahoon et al., 2009). We evaluated patches using six broad geomorphic settings: open coast, back-barrier lagoon marsh, estuarine embayment, estuarine brackish marsh, tidal fresh marsh, and nontidal brackish marsh. When a patch was situated in multiple broad settings, we recorded the primary (dominant) setting, followed by the secondary and tertiary settings, if applicable. Settings were based on a classification scheme modified from Reed et al. 2008; based on Cahoon, 2006; Woodroffe, 2002. The classification scheme further refined some broad settings into sub-setting categories; however, we did not assess patch sub-setting.

Sea level trend - We used data from the National Oceanic and Atmospheric Administration's (NOAA) Center for Operational Oceanographic Products and Services (CO-OPS; NOAA Ocean Service, CO-OPS, 2013) to calculate sea level trend for each patch. CO-OPS calculates sea level trends, i.e., changes in mean sea level (rise or fall, mm per year), for long-term water level stations using a minimum of 30 years of consecutive station observations (NOAA Ocean Service, CO-OPS, 2014). We recorded a single trend value for each patch using the trend of the water level station that was located in an area most similar to the patch; this was usually the nearest station and applied to the majority of patches. We used the mean sea level trend of nearby stations to estimate the trend for a patch when no station existed in an area similar to the patch. For example, we recorded the mean sea level trend of Kings Point, Port Jefferson, and Montauk stations as the sea level trend for patches on Long Island's southern shore (Far Rockaway to Southampton, New York) where a long-term water level station is not present.

Human disturbance - We calculated road density as an index of human disturbance using U.S. Census Bureau TIGER/Line road spatial data (U.S. Census Bureau, 2013). We estimated road density by creating a 500-m buffer around each patch, calculating the total road length in the patch and buffer, and dividing by the area of the patch and buffer. Although road presence within tidal marshes is usually minimal, we included patch road length in the calculation so that roads present in patches were accounted for.

Bayes Net Model Development

We developed models to predict occurrence and density for focal species using the BN modeling shell Netica 5.16 (Norsys Software Corp., 2014, Marcot et al., 2006) and the covariates defined above. We grouped the covariates into site, local, landscape, and regional scales (Table 4). The site level contained three covariates measured at the patch scale; the local level contained six covariates measured outside patches up to 500 m; the landscape level contained six covariates measured greater than 500 m from patches up to 1,000 m; and the regional level contained seven covariates measured across the Northeast (Table 4).

We constructed the models in a stepwise fashion and increased model complexity with each step by incorporating covariates from the geographic scales in succession (Table 4). We assessed covariate relationships using Pearson correlation coefficients within each geographic level to determine which covariates to include in the subset models. We did not omit covariates with missing data since an advantage of the BN framework is to incorporate missing data as uncertainty in model probability distributions (Friedman, 1997; Lauritzen, 1995).

We discretized each continuous variable (a node in the BN) into state ranges. We discretized predictor covariates (i.e., patch features) into three or four states (Table 4), occurrence into two states (absent or present), and density into three states (birds per ha): 0, $0 < 1$, and > 1 . We created Tree Augmented Naïve Bayes (TAN) structures to build alternative models from the existing data (Friedman et al., 1997). We parameterized the model structures using the case data, calculating conditional probability values for each covariate using the Expectation Maximization algorithm (EM; Dempster et al., 1977).

Model complexity and performance - We defined model complexity as the number of covariates and probabilities (unconditional priors and conditional probabilities) in each model. We used these two metrics because model complexity metrics are not necessarily correlated and multiple metrics can provide a more complete picture of model structure to assess model parsimony; the more complex a model, the less parsimonious (Marcot, 2012). We assessed model performance by comparing the BNs' most probable predictions for species occurrence and density to our sampled estimates. We compared model classification performance by calculating spherical payoff values and confusion error rates for each model (Marcot, 2012). Spherical payoff is an index ranging from 0 to 1, with 1 indicating perfect model performance (Hand, 1997). For our BNs, models with the greatest spherical payoff performed the best in correctly predicting the state of species occurrence or density. Confusion error rates are the percentage of cases a model classifies incorrectly from the cases' actual state. We calculated confusion error rates from confusion matrices for false positives (Type I error), false negatives (Type II error), and their sum to assess model predictions for our presence/absence and density states (Kohavi and Provost, 1998; Marcot, 2012). Because we constructed, parameterized, and tested our BNs using the same dataset, we used 5-fold cross validation to test the parameterized networks with the case data and evaluate the prediction accuracy and validity of our models (Boyce et al., 2002). We compared performance metrics for the models using the entire existing dataset to the 5-fold results to identify the best models for predicting species occurrence and density; see Appendix A for model evaluation tables.

Model selection and estimating abundance - We selected occurrence models with low false positive error (predicting a species to be present when it was absent) and low total error, and density models with low error for the greatest density state (> 1) and low total error. We used the expected density values from the best-performing models to estimate abundance for each species. We multiplied the expected value for each patch by patch area (ha) and summed across patches to estimate abundance in unsurveyed patches. We added this total to the abundance total for the surveyed patches (Wiest et al. in press) and calculated mean patch abundance. We selected random abundance values from a normal distribution for mean patch abundance to simulate an abundance total for each species by subregion and region-wide. The number of random values equaled the number of patches (surveyed and unsurveyed) where we estimated species abundance. We multiplied the random value for each patch by patch area (ha) and summed across patches to estimate total abundance. We repeated the simulation 5,000 times to calculate a final abundance estimate. We report the mean of the simulated abundance totals as the final abundance estimate and multiplied the standard deviation of the mean by 1.96 to calculate a 95% confidence interval for the total.

Results

Sampling Design

Sampling universe - The primary sampling universe in surveyed subregions (Coastal Maine to Eastern Chesapeake Bay) consisted of 1,110 hexagons containing 280,722 ha of salt marsh (Table 2). The number

of hexagons in each subregion ranged from 88 in Delaware Bay (59,956 ha of salt marsh), to 212 in Eastern Chesapeake Bay (78,337 ha of salt marsh). Because we stratified our sampling effort independent of the extent of salt marsh in a subregion, a large sample of total hexagons did not indicate a large quantity of salt marsh. We excluded 259 hexagons (973 ha of salt marsh) from the initial GRTS hexagon selection since these hexagons each contained less than 10 ha of marsh.

Sampled hexagons - We sampled 277 (135,042 ha of salt marsh) of the 1,110 total hexagons (25%) from Coastal Maine to Eastern Chesapeake Bay. The number of hexagons surveyed in each subregion ranged from 22 in Eastern Chesapeake Bay to 44 in Cape Cod to Casco Bay (Table 2). Marshes owned by state agencies occurred in 127 of the surveyed hexagons; 60 surveyed hexagons contained both state and federally owned marsh; an additional 32 surveyed hexagons contained marsh owned by federal agencies only. Of the 92 surveyed hexagons containing federally owned marsh, 23 hexagons contained NPS-owned marsh, 63 hexagons contained USFWS-owned marsh, and 6 hexagons contained marsh owned by both agencies.

Sampled survey points - We sampled 1,780 survey points in the sampled hexagons. Surveyed points were composed of 1,314 new points and 466 historical points from 18 of the 20 existing projects (Table 3). The number of survey points in each subregion ranged from 119 points in Long Island to 340 points in Cape Cod to Casco Bay (Table 2). The distribution of survey points on public versus private lands was 45% and 55%, respectively. We sampled 1,642 points in 2011, 1,714 points in 2012, and 1,575 points in both years.

Bayes Net Model Covariates

Saltmarsh Patches - We defined 13,332 saltmarsh habitat patches in the Northeast (Table 5). Total patches per subregion ranged from 166 patches in Delaware Bay to 4,927 patches in Western Chesapeake Bay. Delaware Bay had the fewest and largest patches (mean area = 360 ± 145 ha). Patches north and south of Delaware Bay in Coastal New Jersey and Coastal Delmarva also were large and shared similar average area dimensions: roughly 500 patches in each subregion with a mean area of 95 ± 27 ha. Cape Cod to Casco Bay also contained approximately 500 patches, but patches were smaller (38 ± 8 ha). Mean patch areas were smaller in Long Island (14 ± 1 ha) and Eastern Chesapeake Bay (23 ± 9 ha). In Coastal Maine, Southern New England, and Western Chesapeake Bay, saltmarsh patches consisted of over 1,000 patches <10 ha.

Land use and land cover - In patches with high-marsh spatial data, 45% of patches contained no high marsh and 7% of patches contained all high marsh. Mean proportion of high marsh was greatest in Cape Cod to Casco Bay (0.49 ± 0.02). Remote sensing data necessary to classify marsh vegetation into high marsh and non-high marsh areas did not exist for a proportion of the patches in each subregion (29% of total patches = 2,416): Coastal Maine to Delaware Bay – 7% of patches or less, Coastal Delmarva – 16% of patches, and Eastern Chesapeake Bay – 64% of patches.

Table 5. Tidal marsh habitat patches (*n*) and mean (SE) patch covariates in Northeast USA, for eight subregions (north to south).

<i>Category</i>	<i>Covariate</i>	Subregion							
		Coastal Maine	Cape Cod - Casco Bay	Southern New England	Long Island	Coastal New Jersey	Delaware Bay	Coastal Delmarva	Eastern Chesapeake Bay
	Patches (<i>n</i>)	1,441	536	1,201	716	533	166	471	3,341
<i>Dimension</i>									
	Area (ha)	4 (0)	38 (8)	8 (1)	14 (1)	95 (26)	360 (145)	96 (29)	23 (9)
	Perimeter (m)	1,580 (98)	7,269 (1,143)	2,663 (155)	3,883 (310)	10,662 (2,410)	33,502 (11,956)	11,388 (2,613)	2,971 (811)
<i>Land use land cover</i>¹									
	High marsh	0.14 (0.01)	0.49 (0.02)	0.31 (0.01)	0.34 (0.01)	0.14 (0.01)	0.02 (0.0)	0.22 (0.01)	0.22 (0.01)
	Natural 150	0.52 (0.01)	0.39 (0.01)	0.40 (0.01)	0.39 (0.01)	0.25 (0.01)	0.33 (0.02)	0.22 (0.01)	0.25 (0.0)
	Agriculture 150	0.03 (0.0)	0.04 (0.0)	0.01 (0.0)	0.03 (0.0)	0.03 (0.0)	0.19 (0.01)	0.09 (0.01)	0.35 (0.0)
	Developed 150	0.11 (0.0)	0.26 (0.01)	0.30 (0.01)	0.27 (0.01)	0.33 (0.01)	0.12 (0.01)	0.08 (0.01)	0.05 (0.0)
	Open water 150	0.34 (0.01)	0.32 (0.01)	0.28 (0.01)	0.32 (0.01)	0.39 (0.01)	0.36 (0.02)	0.61 (0.02)	0.35 (0.0)
	Marsh 150	0.04 (0.0)	0.10 (0.0)	0.11 (0.0)	0.19 (0.01)	0.10 (0.0)	0.07 (0.01)	0.08 (0.0)	0.08 (0.0)
	Natural 1000	0.50 (0.01)	0.36 (0.01)	0.32 (0.0)	0.29 (0.01)	0.26 (0.01)	0.37 (0.01)	0.26 (0.01)	0.25 (0.0)
	Agriculture 1000	0.03 (0.0)	0.03 (0.0)	0.02 (0.0)	0.04 (0.0)	0.02 (0.0)	0.24 (0.02)	0.12 (0.01)	0.37 (0.0)
	Developed 1000	0.09 (0.0)	0.27 (0.01)	0.31 (0.01)	0.28 (0.01)	0.37 (0.01)	0.14 (0.01)	0.07 (0.0)	0.04 (0.0)
	Open water 1000	0.38 (0.01)	0.33 (0.01)	0.35 (0.01)	0.39 (0.01)	0.35 (0.01)	0.24 (0.02)	0.55 (0.01)	0.33 (0.0)
	Marsh 1000	0.03 (0.0)	0.09 (0.0)	0.07 (0.0)	0.12 (0.0)	0.13 (0.01)	0.17 (0.01)	0.14 (0.0)	0.07 (0.0)
<i>Sea level</i>									
	Sea level trend (mm/yr)	1.95 (0.0)	2.24 (0.02)	2.46 (0.01)	2.61 (0.01)	3.67 (0.02)	3.50 (0.01)	4.39 (0.05)	3.50 (0.0)
<i>Human disturbance</i>									
	Road density	27.58 (0.56)	53.39 (1.56)	52.73 (0.95)	43.4 (1.24)	54.38 (1.76)	28.98 (2.18)	28.23 (1.64)	27.91 (0.37)

¹ Land use land cover covariates are proportions; data was missing for 11 patches for the 150-m buffer calculation and for 6 patches for the 1,000-m buffer calculation.

Across subregions, mean proportion of natural lands and open water typically ranged from 0.25 to 0.50 and mean proportion of agriculture and developed lands ranged from 0.0 to 0.35. Within subregion, mean proportion of natural lands was similar for the 150-m and 1,000-m buffers. The same pattern was true for agriculture, developed lands, and open water. For both buffers, Coastal Maine contained the greatest mean proportion of natural lands; Eastern Chesapeake Bay, agriculture; Coastal New Jersey, developed lands; and Coastal Delmarva, open water. Mean proportion of marsh was greatest in Long Island for the 150-m buffer (0.19 ± 0.01) and in Delaware Bay for the 1,000-m buffer (0.17 ± 0.01), and was lowest in Coastal Maine for both buffers (0.04 ± 0.00 and 0.03 ± 0.00 for 150 m and 1,000 m, respectively).

Geomorphic setting - The primary, broad geomorphic setting was estuarine embayment for 63% of patches ($n = 5,254$), back-barrier lagoon marsh for 27% of patches ($n = 2,296$), and estuarine brackish marsh for 8% of patches ($n = 679$). Minimal patches were classified as tidal fresh marsh ($n = 153$) or open coast ($n = 23$). No patches were classified as nontidal brackish marsh.

Sea level trend - There were 33 NOAA long-term water-level stations in our study area, including all Chesapeake Bay stations. On average, 3.7 stations occurred in each subregion, and six subregions contained two or three stations. Southern New England contained the greatest number of stations ($n = 6$). Although there were nine stations on the western shore of the Chesapeake Bay, some of these stations informed sea level trend in patches on the Bay's eastern shore. Sea level has been rising over the past 30 years for all stations, from 1.76 mm per year (Seavey Island, Maine) to 6.05 mm per year (Chesapeake Bay Bridge Tunnel, Virginia). The northernmost (Eastport, Maine) and southernmost (Portsmouth, Virginia) stations had sea level trends of 2.00 and 3.76 mm per year, respectively. Mean sea level trend by subregion ($\pm$ SE) ranged from 1.95 ± 0.0 mm per year in Coastal Maine to 4.39 ± 0.05 mm per year in Coastal Delmarva.

Human disturbance - Road density within 500 m of each patch ranged from 0.0 to 221.70. Road density was 0.0 for 9% of patches ($n = 722$), greater than 0.0 to 50.0 for 66% of patches ($n = 5,569$), and greater than 50.0 for 25% of patches ($n = 2,114$). Overall, mean road density was greater in northern subregions than in southern subregions and was greatest in Coastal New Jersey (54.38 ± 1.76).

Tidal Marsh Bird Distribution and Abundance

SGCN Species - We estimated the distribution and abundance for 18 SGCN species breeding in the Northeast (Table 6). Confidence intervals for abundance estimates were relatively high as the marshbird sampling protocol we used is designed specifically for secretive marshbirds and not all species using tidal marsh habitat. These results do however, provide the relative contribution of the tidal marsh habitat in each state in supporting SGCN species. Black Rail detections were too infrequent (10 detections over two years) to estimate abundance or trends, despite call-back surveys across USFWS Region 5, indicating a complete collapse of these Mid-Atlantic populations.

Generally, the southern states (NJ, DE, MD, and VA) in the region tended to support greater abundances (total number of individuals) of SGCN individuals than northern states (NY, CT, RI, MA, NH, and ME). American Black Duck, Forster's Tern, Great Blue Heron, Glossy Ibis, Great Egret, and Laughing Gull had the greatest abundances in NJ, DE, MD, and VA (Table 6). Black-crowned and Yellow-crowned Night-herons had the greatest abundance in NY and NJ. Common Tern was most abundant in NY, NJ, MA and VA. Little Blue Heron, a species with a more southerly range, was most common in MD and VA (Table 6). Least

Bittern and Swamp Sparrow were most abundant in NJ, DE, and MD (Table 6). Notably, VA tidal marshes support the greatest abundance of Virginia Rail (Table 6). American Black Duck density (birds / ha) was

Table 6. Estimated abundance¹ ($\pm 95\%$ CI²) of tidal marsh species of greatest conservation need by state within USFWS Region 5, based on field observations and modeling³, 2011-2012, shaded by quartile.

Species	State										Northeast
	ME	NH	MA	RI	CT	NY	NJ	DE	MD	VA	
American Black Duck	1,506 (8,144)	0 ⁴	662 (5,274)	0	74 (444)	515 (3,961)	1,366 (2,334)	2,089 (347)	12,123 (6,650)	4,001 (3,819)	22,162 (68,997)
Black-crowned Night-Heron ⁵	0	0	21 (259)	13 (139)	84 (515)	732 (3,461)	340 (5,056)	0	173 (1,280)	0	2,245 (26,663)
Common Tern	732 (7,919)	46 (4)	5,287 (38,082)	137 (511)	238 (616)	16,244 (54,405)	14,401 (19,172)	526 (952)	244 (554)	5,037 (1,572)	46,506 (268,298)
Common Yellowthroat	3,942 (5,441)	113 (129)	5,215 (5,284)	341 (491)	565 (660)	4,444 (7,333)	22,601 (8,720)	26,859 (4,026)	44,374 (24,123)	4,117 (3,508)	110,482 (62,425)
Forster's Tern	0	69 (5)	13 (100)	0	0	1,492 (7,838)	30,138 (20,979)	12,293 (3,611)	33,854 (64,857)	48,524 (10,560)	101,970 (70,865)
Great Blue Heron	415 (1,292)	146 (129)	650 (908)	74 (271)	54 (105)	280 (1,156)	2,588 (2,864)	6,332 (1,995)	6,567 (6,800)	1,164 (2,377)	16,937 (15,617)
Glossy Ibis	137 (1,086)	91 (7)	698 (3,121)	455 (982)	170 (906)	1,752 (4,235)	10,069 (18,362)	2,649 (2,653)	19,962 (15,302)	2,270 (2,365)	33,087 (48,129)
Great Egret ⁶	192 (343)	274 (22)	1,673 (3,130)	1,197 (2,120)	715 (1,235)	5,546 (10,167)	56,970 (36,981)	4,968 (5,712)	8,690 (7,439)	5,859 (4,713)	83,168 (94,066)
Laughing Gull ⁷	183 (3,299)	0	58 (195)	0	0	4296 (18,431)	166,567 (199,493)	2,588 (1,921)	45,189 (37,744)	210,743 (462,625)	366,814 (910,510)
Little Blue Heron	30 (100)	0	0	13 (39)	67 (115)	85 (508)	339 (1403)	0	643 (1,960)	406 (591)	1,113 (3,917)
Least Bittern ⁷	0	0	0	0	0	0	636 (184)	348 (58)	2,560 (2,082)	0	3,182 (1,450)
Marsh Wren ⁷	1,066 (3,177)	382 (137)	816 (1,885)	0	3,862 (4,607)	5,621 (24,797)	94,987 (36,074)	41,836 (6,385)	132,831 (47,170)	6,429 (6,793)	274,031 (129,583)
Snowy Egret	1,989 (2,272)	261 (27)	1,954 (2,834)	183 (357)	605 (1,505)	3,522 (6,642)	26,078 (22,526)	5,416 (2,567)	14,006 (12,053)	8,208 (12,808)	58,972 (61,154)

Table 6. Continued

Species	State										Northeast
	ME	NH	MA	RI	CT	NY	NJ	DE	MD	VA	
Swamp Sparrow	670 (2,164)	0 ⁴	0	0	465 (679)	614 (3,464)	2,745 (4,087)	3,232 (1,313)	9,150 (3,132)	188 (788)	16,900 (22,896)
Tricolored Heron	0	0	0	0	33 (59)	19 (186)	2,933 (1,840)	0	1,858 (5,273)	3,534 (3,383)	6,884 (8,103)
Virginia Rail	65 (426)	16 (29)	230 (381)	26 (91)	51 (134)	0	186 (39)	174 (29)	8,703 (3,175)	552 (311)	9,360 (4,774)
Willow Flycatcher	54 (357)	0	247 (1,872)	30 (157)	351 (552)	1,330 (4,696)	1,668 (2,258)	1903 (392)	0	0	6,098 (20,289)
Yellow-crowned Night-Heron	0	0	31 (566)	0	15 (109)	913 (3,214)	1,001 (1,825)	0	0	0	1,797 (12,057)

¹ Estimates of abundance based on density estimates from surveyed patches extrapolated to un-surveyed patches to yield statewide population estimate.

² Calculated using 5000 bootstraps. Note: lower boundaries of 95% confidence intervals not truncated at zero.

³ Using Unmarked in Program R (Fisk and Chandler 2011).

⁴ Insufficient data to estimate abundance.

⁵ Model returned high estimates for some patches in each state in 2012, so substituted statewide average density from other patches to estimate abundance. See text for methods.

⁶ Model did not converge in 2011, so estimate based on 2012 data only.

⁷ Model did not converge in 2012, so estimate based on 2011 data only.

Table 7. Mean density¹ (birds/ha) of 18 Species of Greatest Conservation Need within surveyed patches of salt marsh during the breeding season, 2011-2012.

Species		State									
		ME	NH	MA	RI	CT	NY	NJ	DE	MD	VA
American Black Duck	Density	0.21	NA ⁴	0.08	NA	0.02	0.06	0.02	0.01	0.11	0.12
	SE ²	0.07	NA	0.05	NA	0.02	0.03	0.01	0.01	0.03	0.06
	N ³	167	26	97	36	58	73	70	10	24	21
Black-crowned Night-Heron	Density	n/a	NA	<0.01	0.01	0.03	0.08	0.01	NA	0.01	0
	SE	NA	NA	<0.01	0.01	0.02	0.03	0.01	NA	0.01	0
	N	166	26	96	36	56	70	58	9	24	21
Common Tern	Density	0.11	<0.01	0.52	0.09	0.06	1.19	0.19	0.05	<0.01	0.04
	SE	0.07	<0.01	0.35	0.05	0.02	0.47	0.10	0.03	<0.01	0.02
	N	167	26	97	36	58	73	70	10	24	21
Common Yellowthroat	Density	0.49	0.09	0.29	0.24	0.13	0.47	0.26	0.40	0.47	0.14
	SE	0.05	0.03	0.05	0.05	0.02	0.06	0.04	0.14	0.12	0.05
	N	167	26	97	36	58	73	70	10	24	21
Forster's Tern	Density	NA	<0.01	<0.01	NA	NA	0.09	0.32	0.47	0.98	0.64
	SE	NA	<0.01	<0.01	NA	NA	0.07	0.11	0.12	0.32	0.16
	N	167	26	97	36	58	73	70	10	24	21
Great Blue Heron	Density	0.05	0.07	0.02	0.05	0.01	0.02	0.06	0.20	0.08	0.05
	SE	0.01	0.03	0.01	0.03	<0.01	0.01	0.01	0.07	0.03	0.04
	N	167	26	97	36	58	73	70	10	24	21
Glossy Ibis	Density	0.01	<0.01	0.03	0.17	0.04	0.12	0.15	0.15	0.26	0.06
	SE	0.01	<0.01	0.03	0.09	0.03	0.04	0.09	0.09	0.08	0.04
	N	167	26	97	36	58	73	70	10	24	21
Great Egret	Density	<0.01	<0.01	0.12	0.51	0.17	0.44	0.47	0.24	0.12	0.16
	SE	<0.01	<0.01	0.03	0.20	0.04	0.09	0.19	0.20	0.04	0.07
	N	163	26	97	36	52	72	69	10	24	21
Laughing Gull	Density	0.03	NA	<0.01	NA	NA	0.39	2.48	0.16	0.86	9.47
	SE	0.03	NA	<0.01	NA	NA	0.17	1.01	0.07	0.19	7.05
	N	161	26	95	34	58	55	68	10	24	21
Little Blue Heron	Density	<0.01	NA	NA	<0.01	<0.01	0.01	0.01	NA	0.02	0.01
	SE	<0.01	NA	NA	<0.01	<0.01	<0.01	0.01	NA	0.01	0.01
	N	167	26	97	36	58	73	70	10	24	21

Table 7. Continued.

Species		State									
		ME	NH	MA	RI	CT	NY	NJ	DE	MD	VA
Least Bittern	Density	NA ⁴	NA	NA	NA	NA	NA	<0.01	<0.01	0.02	0
	SE ²	NA	NA	NA	NA	NA	NA	<0.01	<0.01	0.01	0
	N ³	161	26	95	34	58	55	68	10	24	21
Marsh Wren	Density	0.05	0.05	0.03	<0.01	0.58	0.60	1.06	0.29	0.63	0.13
	SE	0.03	0.03	0.02	<0.01	0.16	0.23	0.18	0.22	0.23	0.10
	N	161	26	95	34	58	55	68	10	24	21
Snowy Egret	Density	0.08	0.01	0.11	0.13	0.14	0.25	0.24	0.21	0.22	0.29
	SE	0.02	0.01	0.03	0.03	0.05	0.06	0.11	0.09	0.06	0.20
	N	167	26	97	36	58	73	70	10	24	21
Swamp Sparrow	Density	0.06	NA	NA	NA	0.05	0.05	0.06	0.07	0.03	0.02
	SE	0.02	NA	NA	NA	0.02	0.03	0.02	0.05	0.02	0.01
	N	167	26	97	36	58	73	70	10	24	21
Tricolored Heron	Density	NA	NA	NA	NA	<0.01	<0.01	0.01	NA	0.05	0.11
	SE	NA	NA	NA	NA	<0.01	<0.01	0.01	NA	0.03	0.05
	N	167	26	97	36	58	73	70	10	24	21
Virginia Rail	Density	<0.01	0.01	<0.01	0.01	<0.01	n/a	<0.01	<0.01	0.04	<0.01
	SE	<0.01	0.01	<0.01	0.01	<0.01	n/a	<0.01	<0.01	0.02	<0.01
	N	167	26	97	36	58	73	70	10	24	21
Willow Flycatcher	Density	0.01	NA	0.02	0.03	0.08	0.12	0.04	0.02	NA	NA
	SE	<0.01	NA	0.02	0.01	0.02	0.04	0.01	0.01	NA	NA
	N	167	26	97	36	58	73	70	10	24	21
Yellow-crowned Night-Heron	Density	NA	NA	0.01	NA	<0.01	0.07	0.02	NA	NA	NA
	SE	NA	NA	0.01	NA	<0.01	0.03	0.01	NA	NA	NA
	N	167	26	97	36	58	73	70	10	24	21

¹ Density was estimated by patch using "Unmarked" in Program R based on detections of focal species detections within 0-100 m during 5-min passive point counts.

² Standard Error.

³ Number of patches surveyed during 2011-2012 where density was estimated.

⁴ None detected within state.

greatest in ME followed by MD and VA (Table 7). Forster's Tern, Marsh Wren and Snowy Egret had greatest densities in NY, NJ, DE, MD, and VA (Table 7). Glossy Ibis density was greatest in MD (Table 7).

Clapper Rail - We developed BNs for Clapper Rail using cases for 255 surveyed marsh patches. Occurrence models contained 74 to 832 probabilities, spherical payoff values ranged from 0.869 to 0.918, and total confusion error was between 10.2 and 17.3%. The final-selected model (Sub 3) predicted Clapper Rails occurred in 343 patches (6% of patches; Table 8). Clapper rails were most common in Delaware Bay and least common in Southern New England, occurring on 19% and 2% of the patches respectively (Table 9). Density models for Clapper Rail contained 111 to 1,248 probabilities, spherical payoff values ranged from 0.822 to 0.903, and total confusion error was between 12.6 and 23.5%. The final-selected model (All 4) predicted the Clapper Rail density >1 birds per ha in 309 (6%) of the patches (Table 10). We estimated 109,758 Clapper Rails in the Northeast with 49% of the population occurring in Coastal Delmarva (Table 11).

Willet - We developed BNs for Willet using cases for 582 surveyed marsh patches. Occurrence models contained 74 to 1,156 probabilities, spherical payoff values ranged from 0.836 to 0.895, and total confusion error was between 13.1 and 19.9%. The final-selected model (All 4) predicted Willets occurred in 1,132 patches (13% of patches; Table 8). Willets were most common in Coastal Delmarva and least common in Coastal Maine, occurring on 37% and 1% of the patches respectively (Table 9). Density models for Willet contained 111 to 1,734 probabilities, spherical payoff values ranged from 0.809 to 0.866, and total confusion error was between 15.8 and 22.5%. The final-selected model (All 4) predicted the Willet density >1 birds per ha in 360 (4%) of the patches (Table 10). We estimated 111,021 Willets in the Northeast with 54% of the population occurring in Delaware Bay and Coastal Delmarva (Table 11).

Nelson's Sparrow - We developed BNs for Nelson's sparrow using cases for 193 surveyed marsh patches. Occurrence models contained 74 to 336 probabilities, spherical payoff values ranged from 0.857 to 0.906, and total confusion error was between 10.9 and 18.1%. The final-selected model (All 3) predicted Nelson's sparrows occurred in 206 patches (12% of patches; Table 8). Nelson's sparrows were similarly distributed in Cape Cod to Casco Bay and Coastal Maine, occurring on 14% and 12% of the patches respectively (Table 9). Density models for Nelson's sparrow contained 111 to 531 probabilities, spherical payoff values ranged from 0.815 to 0.906, and total confusion error was between 10.9 and 23.8%. The final-selected model (All 4) predicted the Nelson's sparrow density >1 birds per ha in 163 (10%) of the patches (Table 10). We estimated 6,640 Nelson's sparrows in the Northeast with 70% of the population occurring in Coastal Maine (Table 11).

Saltmarsh Sparrow - We developed BNs for Saltmarsh Sparrow using cases for 509 surveyed marsh patches. Occurrence models contained 74 to 1,194 probabilities, spherical payoff values ranged from 0.748 to 0.917, and total confusion error was between 10.6 and 35.2%. The final-selected model (All 4) predicted Saltmarsh Sparrows occurred in 2,482 patches (33% of patches; Table 8). Saltmarsh sparrows were most common in Long Island (99% of patches) and Southern New England (96% of patches) and least common in Coastal Maine (4% of patches, Table 11). Density models for Saltmarsh Sparrow contained 111 to 1,815 probabilities, spherical payoff values ranged from 0.708 to 0.895, and total confusion error was between 12.8 and 39.9%. The final-selected model (All 4) predicted the Saltmarsh Sparrow density >1 birds per ha in 328 (4%) of the patches (Table 10). We estimated 60,058 Saltmarsh Sparrows in the

Northeast with 53% of the population occurring in Coastal New Jersey and Eastern Chesapeake Bay (Table 11).

Seaside Sparrow - We developed BNs for Seaside Sparrow using cases for 390 surveyed marsh patches. Occurrence models contained 74 to 914 probabilities, spherical payoff values ranged from 0.805 to 0.912, and total confusion error was between 10.8 and 26.7%. The final-selected model (All 4) predicted Seaside Sparrows occurred in 1,294 patches (19% of patches; Table 8). Seaside sparrows were most common in Long Island and least common in Cape Cod to Casco Bay, occurring on 50% and 2% of the patches respectively (Table 9). Density models for Seaside Sparrow contained 111 to 1,365 probabilities, spherical payoff values ranged from 0.773 to 0.903, and total confusion error was between 11.5 and 30.3%. The final-selected model (Sub 4) predicted the Seaside Sparrow density >1 birds per ha in 169 (3%) of the patches (Table 10). We estimated 234,542 Seaside Sparrows in the Northeast with 73% of the population occurring in Delaware Bay and Eastern Chesapeake Bay (Table 11).

Table 8. Model complexity and classification performance of the best-performing Bayesian network models predicting species occurrence or density (birds per ha) as a function of tidal marsh habitat patch covariates for tidal-marsh-specialist bird species in Northeast USA. Models were selected from a group of seven models for each response variable-species combination; for model complexity and classification performance results, including 5-fold cross validation results, for all tested models.

Response variable Species	Model ¹	Spherical payoff	Model complexity		Model performance, confusion error rates, % (n)						
			No. covs.	No. probs.	Absent	Present	Total ²	0	>0 - 1	>1	Total ^b
Occurrence											
Clapper Rail	Sub 3	0.905	11	230	10.4 (17)	14.3 (13)	11.8 (30)				
Willet	All 4	0.895	22	1,156	10.6 (44)	19.4 (32)	13.1 (76)				
Nelson's Sparrow	All 3	0.905	15	308	7.4 (10)	19.3 (11)	10.9 (21)				
Saltmarsh Sparrow	All 4	0.917	22	1,194	13.9 (32)	7.9 (22)	10.6 (54)				
Seaside Sparrow	All 4	0.912	22	914	8.2 (22)	16.3 (20)	10.8 (42)				
Density											
Clapper Rail	All 4	0.903	22	1,248				9.1 (15)	19.7 (14)	15.0 (3)	12.6 (32)
Willet	All 4	0.866	22	1,734				6.5 (27)	32.5 (39)	57.8 (26)	15.8 (92)
Nelson's Sparrow	All 4	0.898	22	531				5.1 (7)	23.5 (8)	30.4 (7)	11.4 (22)
Saltmarsh Sparrow	All 4	0.895	22	1,815				12.6 (29)	11.9 (30)	22.2 (6)	12.8 (65)
Seaside Sparrow	Sub 4	0.862	16	528				10.1 (27)	34.8 (32)	19.4 (6)	16.7 (65)

¹ Number of cases in each species dataset used to parameterize the models: Clapper Rail = 255, Willet = 582, Nelson's Sparrow = 193, Saltmarsh Sparrow = 509, and Seaside Sparrow = 390.

² The percent error of the absent and present states, or, the three density states, equals 100% of total error.

Table 9. Number of tidal marsh habitat patches where the best-performing Bayesian network models predicted the most probable occurrence state for tidal-marsh-specialist bird species in Northeast USA, by subregion (north to south) and region-wide. Percent of patches relative to the number of patches analyzed within a subregion is in parentheses.

<i>Species</i> ¹ Occurrence state	Subregion								
	Coastal Maine	Cape Cod - Casco Bay	Southern New England	Long Island	Coastal New Jersey	Delaware Bay	Coastal Delmarva	Eastern Chesapeake Bay	Northeast USA
Clapper Rail									
Absent	NA ²	NA	389 (98%)	672 (94%)	450 (84%)	135 (81%)	396 (84%)	3,238 (97%)	5,280 (94%)
Present			7 (2%)	44 (6%)	83 (16%)	31 (19%)	75 (16%)	103 (3%)	343 (6%)
Willet									
Absent	1,433 (99%)	462 (87%)	986 (82%)	550 (77%)	447 (84%)	115 (69%)	298 (63%)	2,980 (89%)	7,271 (87%)
Present	8 (1%)	72 (13%)	215 (18%)	166 (23%)	86 (16%)	51 (31%)	173 (37%)	361 (11%)	1,132 (13%)
Nelson's Sparrow									
Absent	1,265 (88%)	178 (86%)	NA	NA	NA	NA	NA	NA	1,443 (88%)
Present	176 (12%)	30 (14%)							206 (12%)
Saltmarsh Sparrow									
Absent	606 (96%)	400 (75%)	44 (4%)	9 (1)	480 (90%)	134 (81%)	372 (79%)	3,064 (92%)	5,109 (67%)
Present	23 (4%)	134 (25%)	1,157 (96%)	707 (99%)	53 (10%)	32 (19%)	99 (21%)	277 (8%)	2,482 (33%)
Seaside Sparrow									
Absent	NA	321 (98%)	1,135 (95%)	355 (50%)	454 (85%)	137 (83%)	364 (77%)	2,695 (81%)	5,461 (81%)
Present		6 (2%)	66 (5%)	361 (50%)	79 (15%)	29 (17%)	107 (23%)	646 (19%)	1,294 (19%)

¹ Occurrence was predicted for patches south of 41.3390°N for Clapper Rail; north of 42.8520°N for Nelson's Sparrow; south of 44.0753°N for Saltmarsh Sparrow; and south of 42.9185°N for Seaside Sparrow.

² NA = not applicable.

Table 10. Number of tidal marsh habitat patches where the best-performing Bayesian network models predicted the most probable density state (birds per ha) for tidal-marsh-specialist bird species in Northeast USA, by subregion (north to south) and region-wide. Percent of patches relative to the number of patches analyzed within a subregion is in parentheses.

Species ¹	Density state	Subregion								
		Coastal Maine	Cape Cod - Casco Bay	Southern New England	Long Island	Coastal New Jersey	Delaware Bay	Coastal Delmarva	Eastern Chesapeake Bay	Northeast USA
Clapper Rail	0	NA	NA	346 (89%)	672 (94%)	443 (83%)	96 (58%)	258 (55%)	3,038 (91%)	4,853 (86%)
	>0 - 1			31 (8%)	32 (4%)	66 (12%)	67 (40%)	106 (23%)	152 (5%)	454 (8%)
	>1			13 (3%)	11 (2%)	24 (5%)	3 (2%)	107 (23%)	151 (5%)	309 (6%)
Willet	0	1,431 (99%)	476 (89%)	1,018 (85%)	557 (78%)	420 (79%)	121 (73%)	195 (41%)	3,217 (96%)	7,435 (88%)
	>0 - 1	9 (1%)	52 (10%)	115 (10%)	53 (7%)	41 (8%)	39 (23%)	176 (37%)	123 (4%)	608 (7%)
	>1	1 (0%)	6 (1%)	68 (6%)	106 (15%)	72 (14%)	6 (4%)	100 (21%)	1 (0%)	360 (4%)
Nelson's Sparrow	0	1,189 (83%)	184 (89%)	NA	NA	NA	NA	NA	NA	1,373 (84%)
	>0 - 1	83 (6%)	21 (10%)							104 (6%)
	>1	161 (11%)	2 (1%)							163 (10%)
Saltmarsh Sparrow	0	609 (97%)	380 (71%)	27 (2%)	7 (1%)	461 (86%)	98 (59%)	336 (71%)	2,934 (88%)	4,852 (64%)
	>0 - 1	20 (3%)	148 (28%)	1,132 (94%)	681 (95%)	63 (12%)	20 (12%)	87 (18%)	260 (8%)	2,411 (32%)
	>1	0 (0%)	6 (1%)	42 (3%)	28 (4%)	9 (2%)	48 (29%)	48 (10%)	147 (4%)	328 (4%)
Seaside Sparrow	0	NA	324 (99%)	1,162 (97%)	444 (62%)	461 (86%)	140 (84%)	389 (83%)	3,136 (94%)	6,056 (90%)
	>0 - 1		3 (1%)	35 (3%)	269 (38%)	47 (9%)	22 (13%)	44 (9%)	110 (3%)	530 (8%)
	>1		0 (0%)	4 (0%)	3 (0%)	25 (5%)	4 (2%)	38 (8%)	95 (3%)	169 (3%)

¹ Density was predicted for patches south of 41.3390°N for Clapper Rail; north of 42.8520°N for Nelson's Sparrow; south of 44.0753°N for Saltmarsh Sparrow; and south of 42.9185°N for Seaside Sparrow.

² NA = not applicable.

Table 11. Estimated abundance (95% CI; number of birds) for tidal-marsh-specialist bird species in each state. NA, not applicable.

Species ^a	State									
	Maine	New Hampshire	Mass.	Rhode Island	Connecticut	New York	New Jersey	Delaware	Maryland	Virginia
Clapper rail	NA	NA	187 (±154)	35 (±44)	146 (±120)	1,655 (±544)	34,064 (±24,974)	7,669 (±7,586)	10,735 (±5,953)	55,095 (±41,008)
Willet	1,722 (±1,424)	1,012 (±1,946)	5,103 (±3,188)	519 (±368)	801 (±615)	5,400 (±2,086)	42,291 (±26,089)	13,026 (±14,037)	13,916 (±7,229)	27,210 (±27,530)
Nelson's sparrow	6,423 (±2,754)	239 (±218)	NA	NA	NA	NA	NA	NA	NA	NA
Saltmarsh sparrow	1,620 (±1,216)	1,080 (±1,692)	6,152 (±2,745)	888 (±335)	1,592 (±798)	5,260 (±1,261)	19,940 (±13,632)	4,118 (±4,389)	15,071 (±13,399)	4,224 (±2,553)
Seaside sparrow	NA	NA	316 (±312)	24 (±22)	1,026 (±1,499)	2,964 (±891)	88,378 (±63,412)	36,831 (±54,117)	82,543 (±85,448)	20,992 (±21,582)

^a Abundance estimates are for patches south of 41.3390°N for clapper rail; north of 42.8520°N for Nelson's sparrow; south of 44.0753°N for saltmarsh sparrow; and south of 42.9185°N for seaside sparrow. Estimates are for all patches for willet.

Conclusions

The distribution of the 18 SGCN species for which we could estimate density and abundance was weighted to the southern states (Table 12). New York supported more than 50% of one species population (Black-crowned Night-Heron) as well as a large proportion of Common Tern populations; New Jersey supported more than 50% of two species populations (Great Egret and Yellow-crowned Night-Heron) and large proportions of Common Tern, Laughing Gull, Little Blue Heron, Marsh Wren, Snowy Egret, Tricolored Heron, and Willow Flycatcher populations; Delaware supported large proportions of Common Yellow-throat, Great Blue Heron and Willow Flycatcher populations; Maryland supported more than 50% of five species populations (American Black Duck, Glossy Ibis, Least Bittern, Swamp Sparrow, and Virginia Rail) and large proportions of Common Yellow-throat, Forster's Tern, Great Blue Heron, Marsh Wren, and Snowy Egret; Virginia supported large proportions of Forster's Tern, Laughing Gull, Little Blue Heron, and Tricolored Heron populations (Table 12). Overall SGCN species richness ranged from 14 in NH to 25 in NJ (Table 13).

Our Bayesian approach to predict tidal marsh bird distribution and population estimates provides the first comprehensive estimates for these species in Northeast USA. We predicted species occurrence and density with reasonable accuracy with BNs based on patch covariates at multiple spatial scales (Wiest 2015). Our best-performing predictive BNs provide population size estimates to determine the relative importance of each Northeast subregion and state in supporting breeding populations for these species. Long-term monitoring and conservation planning for tidal marsh birds are necessary to alleviate population declines related to climate change, and our BN models provide a flexible framework built on baseline monitoring and spatial data that can be modified into an adaptive management tool for this purpose (Nyberg et al., 2006).

Our results show that overall, large expansive marsh complexes from Coastal New Jersey to Eastern Chesapeake Bay supported the majority of Clapper Rail, Willet, Saltmarsh Sparrow, and Seaside Sparrow individuals. Species were most common in Long Island (and Seaside sparrows), Delaware Bay (Clapper Rail), and Coastal Delmarva (Willet). Density and total abundance were greatest within the same subregion for two species, Coastal Delmarva for Clapper Rail and Willet (Willet abundance was slightly lower in Coastal Delmarva than in Delaware Bay, but similar). Saltmarsh sparrow density was greatest in Delaware Bay while Saltmarsh Sparrow abundance was greatest in Coastal New Jersey and Eastern Chesapeake Bay. Seaside sparrow density was greatest in Coastal Delmarva while Seaside Sparrow abundance was greatest in Eastern Chesapeake and Delaware Bays. North of the last glacial maximum, including all of Long Island, where marshes are characteristically smaller in area, Long Island and Cape Cod to Casco Bay hosted the greatest abundances for these species. When species' population sizes were assessed in a state-context, New Jersey supported the greatest abundance for three species (i.e., Willet, Saltmarsh Sparrow, and Seaside Sparrow) and Virginia supported half of the region's Clapper Rails.

Our models' greatest performance difficulties occurred in correctly classifying 'present' for occurrence and '>1' for density. Our training dataset contained fewer records for these states compared to the other response categories and including additional known cases where species are present at >1 densities should improve model accuracy. The misclassifications need to be minimized to avoid misrepresenting species distribution and inflating abundance estimates; therefore, we prioritized selecting models with the lowest error rates for the 'present' and '>1' states as they are the most critical from a species monitoring perspective. Our population estimates coincided well with the abundance estimates for sampled, occupied patches (Wiest et al. in press), since the surveyed patches that served as case data to build the BNs constituted a large percent of the total marsh in the study area.

Table 12. Percent of northeast regional population of tidal marsh birds occurring in each of 10 states, based on field observations¹ and modeling², 2011-2013.

Species	State									
	ME	NH	MA	RI	CT	NY	NJ	DE	MD	VA
Clapper Rail	0	0	<1	<1	<1	2	31	7	10	50 ³
Willet	2	<1	5	<1	<1	5	38	12	13	25
Nelson's Sparrow	96	4	0	0	0	0	0	0	0	0
Saltmarsh Sparrow	3	2	10	1	3	9	33	7	25	7
Seaside Sparrow	0	0	<1	<1	<1	1	38	16	35	9
American Black Duck	7	0	3	0	<1	2	6	9	54	18
Black-crowned Night-Heron	0	0	2	<1	6	54	25	0	13	0
Common Tern	2	<1	12	<1	<1	38	34	1	<1	12
Common Yellowthroat	3	<1	5	<1	<1	4	20	24	39	4
Forster's Tern	0	<1	<1	0	0	1	24	10	27	38
Great Blue Heron	2	<1	4	<1	<1	2	14	35	36	6
Glossy Ibis	<1	<1	2	1	<1	5	26	7	52	6
Great Egret	<1	<1	2	1	<1	6	66	6	10	7
Laughing Gull	<1	0	<1	0	0	1	39	<1	11	49
Little Blue Heron	2	0	0	<1	4	5	21	0	41	26
Least Bittern	0	0	0	0	0	0	18	10	72	0
Marsh Wren	<1	<1	<1	0	1	2	33	15	46	2
Snowy Egret	3	<1	3	<1	<1	6	42	9	23	13
Swamp Sparrow	4	0	0	0	3	4	16	19	54	1
Tricolored Heron	0	0	0	0	<1	<1	35	0	22	42
Virginia Rail	<1	<1	2	<1	<1	0	2	2	87	6
Willow Flycatcher	<1	0	4	<1	6	24	30	34	0	0
Yellow-crowned Night-Heron	0	0	2	0	<1	47	51	0	0	0

¹ Data from 5-minute, passive point counts, within 0-100 m from observer.

² Using Bayesian methods for 5 focal species; using Unmarked in Program R for 18 remaining species.

³ Shaded values are the largest percentages contributing to the "first" 50% of regional population.

Our assessment for Nelson's sparrow distribution and abundance occurred over a smaller geographic area compared to the other specialist species due to Nelson's sparrow's relatively limited coastal range in the United States (Hodgman et al., 2002). Nelson's sparrows were similarly distributed in Cape Cod to Casco Bay and Coastal Maine, but occurred at the greatest density and abundance in Coastal Maine. However, Cape Cod to Casco Bay supported 30% of the population, indicating that patches at range peripheries can support substantial local populations.

Our findings highlight the importance of expansive marshes to tidal marsh bird populations and our ability to maintain these areas as viable habitats will likely determine the future persistence of these species in the Northeast. Some of these larger patches are already degrading at high rates and losing habitat due to

accelerated sea level rise and land subsidence, particularly marshes in Dorchester County, Maryland, including Blackwater National Wildlife Refuge and Fishing Bay Wildlife Management Area (Kearney, 2008; Kearney et al., 2002). These marshes should have a greater opportunity for marsh transgression due to the more gradual elevation gradient to adjacent uplands, as well as upland borders consisting of soft edges (e.g., agricultural fields, forest; Scavia et al., 2002). Many of the marsh systems are sediment deprived (Kearney et al., 1988; Mariotti and Fagherazzi, 2013; Stammermann and Piasecki, 2012) and require sediment augmentation to maintain marsh elevation and/or achieve successful transgression (Mariotti and Fagherazzi, 2013; Nittrouer et al., 2012).

Although preservation of sizable, Mid-Atlantic marsh patches is critical for maintaining most specialist-bird populations in the Northeast, marshes on Long Island and northward also are vital for the tidal marsh birds considered most at risk from accelerated sea level rise. Saltmarsh sparrow is formally listed as globally vulnerable (IUCN Red List; BirdLife International, 2015) and the estimated population size prior to this study was between 30,000 and 50,000 individuals (Elphick et al., 2009). We estimated 60,000 individuals, with almost 30% of the population occurring in New England and Long Island marshes. Saltmarsh sparrows nest low to the ground in the high marsh zone and breeding success is closely tied to the lunar tidal cycle (Greenberg et al., 2006). The species is subject to frequent nest failure from tidal flooding and coastal storm events (Gjerdrum et al., 2008a; Shriver et al., 2007), and the effects of climate change are expected to exacerbate flooding impacts to Saltmarsh Sparrow reproduction (Bayard and Elphick, 2011). While marshes north of the last glacial maximum have fewer opportunities for marsh transgression given the steeper elevation gradient and increased presence of hard shoreline barriers (e.g., development, infrastructure), this area of the Northeast is expected to experience lower rates of sea level rise than the Mid-Atlantic and may prove to be a stronghold of Saltmarsh Sparrow in the future.

We assessed bird densities within the single, broad habitat estuarine emergent marsh and did not distinguish among basic salt marsh zones (e.g., low marsh, high marsh, salt pans, and terrestrial border; Bertness, 1999). Habitat use in marsh vegetation zones and adjacent habitats, such as tidal flats and beaches, differs by species (Hanson and Shriver, 2006; Nocera et al., 2007; Shriver et al., 2010), and marsh birds are typically concentrated in particular areas leading to high spatial variation in abundance within a marsh (Conway and Droege, 2006). Distribution maps typically illustrate species' ranges regardless of the array of habitats used (Kantrud, 1982), and our mapping reflects species distribution and abundance across all saltmarsh habitat regardless of species dependence for marsh vegetation zone. Therefore, our results should not be construed as the overall species distribution in the study area, a caution common to interpreting larger scale species distribution and abundance maps (Kantrud, 1982). Similarly, occurrence maps for some species do not necessarily correspond well with species nesting occurrence maps, as is the case for Saltmarsh Sparrow (Meiman et al., 2012), warranting additional caution for this species. Still, our baseline mapping effort provides wildlife conservation entities with a reasonable means to begin synthesizing the distribution and abundance of tidal marsh birds across this broad geographic area.

A BN approach, such as the one implemented here, is one possible adaptive management framework to be explored (Nyberg et al., 2006; for example application see Howes et al., 2010). BNs are flexible and can be used to evaluate management decisions based on empirical data (Marcot et al., 2001; McCann et al., 2006; Morrison et al., 2006). Networks can be continuously updated with current bird monitoring and spatial data, incorporate variables from improved sea level rise and climate change models, and update and add management decisions based on real-world examples (McCann et al., 2006). A tool that helps identify the importance of local habitat patches to regional bird populations and provides guidance for tidal marsh habitat management decisions, such as felling trees to promote marsh transgression, is necessary to effectively combat species population declines due to climate change.

Table 13. Species richness of tidal marsh birds among 10 northeastern states, based on field observations¹, 2011-2012.

ME	NH	MA	RI	CT	NY	NJ	DE	MD	VA
ABDU	ABDU	ABDU	ABDU	ABDU	ABDU	ABDU	ABDU	ABDU	ABDU
BCNH	n/o ²	BCNH	BCNH	BCNH	BCNH	BCNH	BCNH	BCNH	BCNH
n/o	n/o	n/o	n/o	n/o	n/o	n/o	BLRA	BLRA	n/o
n/o	n/o	n/o	n/o	n/o	n/o	BNST	BNST	BNST	BNST
CLRA	CLRA	CLRA	CLRA	CLRA	CLRA	CLRA	CLRA	CLRA	CLRA
COTE	COTE	COTE	COTE	COTE	COTE	COTE	COTE	COTE	COTE
COYE	COYE	COYE	COYE	COYE	COYE	COYE	COYE	COYE	COYE
n/o	FOTE	FOTE	n/o	n/o	FOTE	FOTE	FOTE	FOTE	FOTE
GBHE	GBHE	GBHE	GBHE	GBHE	GBHE	GBHE	GBHE	GBHE	GBHE
GLIB	GLIB	GLIB	GLIB	GLIB	GLIB	GLIB	GLIB	GLIB	GLIB
GREG	GREG	GREG	GREG	GREG	GREG	GREG	GREG	GREG	GREG
LAGU	n/o	LAGU	LAGU	n/o	LAGU	LAGU	LAGU	LAGU	LAGU
LBHE	n/o	n/o	LBHE	LBHE	LBHE	LBHE	LBHE	LBHE	LBHE
LEBI	n/o	LEBI	n/o	LEBI	n/o	LEBI	LEBI	LEBI	LEBI
MAWR	MAWR	MAWR	MAWR	MAWR	MAWR	MAWR	MAWR	MAWR	MAWR
NESP	NESP	NESP	NESP	NESP	n/o	NESP	n/o	NESP	NESP
SALS	SALS	SALS	SALS	SALS	SALS	SALS	SALS	SALS	SALS
SESP	n/o	SESP	SESP	SESP	SESP	SESP	SESP	SESP	SESP
n/o	n/o	n/o	n/o	n/o	n/o	SEWR	n/o	n/o	n/o
SNEG	SNEG	SNEG	SNEG	SNEG	SNEG	SNEG	SNEG	SNEG	SNEG
SWSP	n/o	n/o	n/o	SWSP	SWSP	SWSP	SWSP	SWSP	SWSP
TRHE	n/o	n/o	n/o	TRHE	TRHE	TRHE	TRHE	TRHE	TRHE
VIRA	VIRA	VIRA	VIRA	VIRA	VIRA	VIRA	VIRA	VIRA	VIRA
WIFL	n/o	WIFL	WIFL	WIFL	WIFL	WIFL	WIFL	WIFL	WIFL
WILL	WILL	WILL	WILL	WILL	WILL	WILL	WILL	WILL	WILL
n/o	n/o	YCNH	n/o	YCNH	YCNH	YCNH	YCNH	n/o	n/o
21	14	20	18	21	21	25	24	24	23

¹ Includes any observations of species during 5-minute passive point count, responses to call-response surveys, and in all distance bands.

² n/o = Not observed during field surveys.

V. Population Trends

Methods

Field and remote imagery data collection

We combined the results of our bird surveys (as described above in section **IV. Distribution and Abundance**) at 1,770 points with a historical survey database of point counts conducted in tidal marshes from Maine to Virginia, a total of 3,064 survey locations monitored variously between 1994 and 2012 (Fig. 2). This historical database includes surveys conducted at 2541 points that were not resurveyed in 2011 and 2012 due to our point selection methodology (as described above). Rachel Carson National Wildlife Refuge (NWR) (2000 – 2012), Parker River NWR (2000 – 2012), Monomoy NWR (2005 – 2012), and

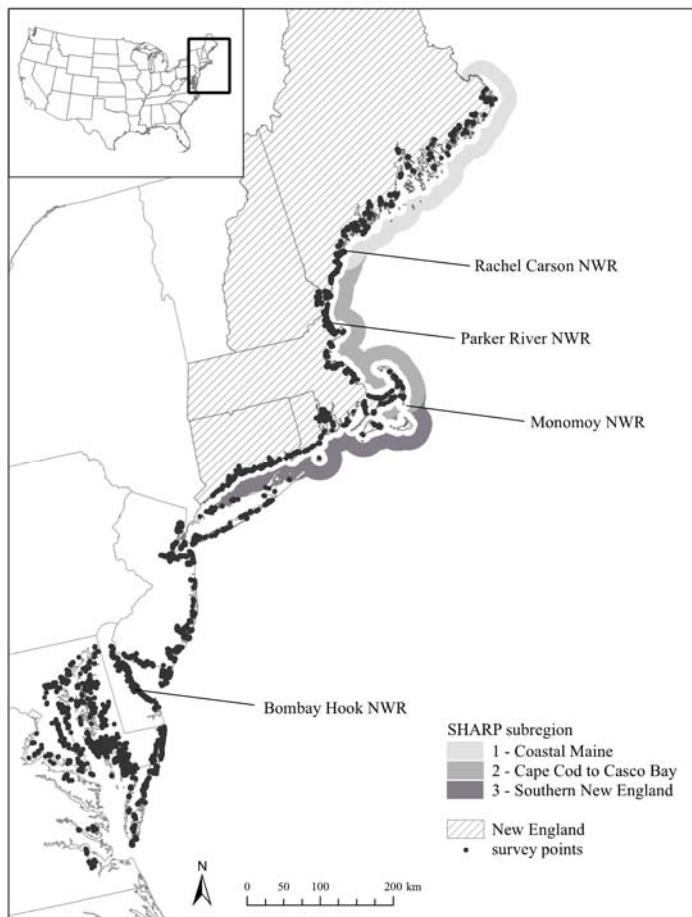


Figure 2. Locations of subregions, National Wildlife Refuges, and survey points used in population trend analyses.

Bombay Hook NWR (1997 – 2007) provided longer term survey data conducted annually. The Maine Department of Inland Fisheries and Wildlife (MDIFW) and Greg Shriver provided additional survey data from 1997 – 2000 (Shriver et al. 2004), conducted in New England tidal marshes. The Smithsonian, Massachusetts Audubon, New Hampshire Audubon, and New Jersey Audubon made additional contributions of historical data (Table 14). All studies followed passive, fixed-point count methodology, and were conducted between sunrise and 11 AM from April 15 to August 15. All surveys recorded the number and species of birds detected by sight or sound within either 50, 100 m (or both) of the survey point for at least five minutes. While some studies (e.g., the contemporary surveys) also recorded birds in distance categories greater than 100 m, for time periods longer than five minutes, or for periods of the year outside of the breeding season, we only used data over the shorter time and spatial scales defined here to maintain consistency across all studies. Except where noted below, we only used data from within 50 m of the survey point.

We collected data on marsh modification around each survey point using Google Earth aerial imagery (Google Inc. 2013). We assessed the relative degree of marsh ditching and Open Marsh Water Management (OMWM; Fig. 3) at 50- and 100-m radius circles around both the contemporary survey points ($n = 1,770$) and all additional historical survey locations ($n = 1,294$). For both OMWM and ditching we recorded their presence or absence at those two spatial scales. To assess degree of ditching, we placed a set of North-South and East-West crosshairs

over each survey point. We then counted the number of ditches that intersected the transects at 50- and 100-m buffers from the survey point. We also recorded the number of tidal restrictions affecting each survey point by counting anthropogenic structures (e.g., bridges, railroads, tide gates, causeways) that spanned the tidal channel downstream from the survey location.

Table 14. Geographic and temporal scope of databases used for analyses of bird population changes across USFWS Region 5.

SHARP subregions	Contributor	Years	Radius of Recorded Detections ¹	
			50 m	100 m
Chesapeake Bay	W. Deluca & P. Marra (Smithsonian)	2002 - 2003	X	
Delaware Bay	Bombay Hook NWR	1994 - 2007	X	
Delaware Bay	R. Greenberg (Smithsonian)	2001 - 2009		X
Casco Bay to Cape Cod	NH Audubon	2007	X	
Coastal Maine	Maine DIFW	1997 - 2000	X	X
Casco Bay to Cape Cod	Maine DIFW	1997 - 2000	X	X
Casco Bay to Cape Cod	Massachusetts Audubon	1999 - 2001, 2005-07		X
Coastal New Jersey	New Jersey Meadowlands Comm.	2005 - 2006		X
Casco Bay to Cape Cod	Monomoy NWR	2005 - 2012	X	X
Casco Bay to Cape Cod	Parker River NWR	2000 - 2012	X	X
Casco Bay to Cape Cod	Rachel Carson NWR	2000 - 2012	X	X
Coastal New Jersey	New Jersey Audubon	2009	X	X
Casco Bay to Cape Cod	G. Shriver	1998 - 2000	X	X
Southern New England	G. Shriver	1998 - 2000	X	X
All Subregions	SHARP	2011 - 2012	X	X

¹ All surveys were point counts with fixed radii of 50 or 100 m (or both) where all birds using the marsh habitat were recorded for five minutes without use of bird vocalization broadcasts

To investigate the importance of marsh modification relative to larger scale changes (e.g., rates of geological plate subsidence, storminess, sea-level rise), we used data from the National Oceanic and Atmospheric Administration's (NOAA) Center for Operational Oceanographic Products and Services (CO-OPS; <http://tidesandcurrents.noaa.gov/>) as a proxy for spatially explicit flooding risk from Maine to Virginia. Specifically we used 30-year averages of sea-level rise trends and 1% exceedance values from monitor buoys along the coast. Exceedance values are the mean tidal height above mean highest high water for a flood with a given frequency. The 1% exceedance values calculated by NOAA CO-OPS, for example, are the flooding heights of a one in a hundred year flooding event. Sites with higher exceedance values thus experience floods of a given height more frequently than sites with lower exceedance values. This metric can therefore serve as a proxy for flooding risk from the combination of astronomical and storm tides. We recorded both exceedance values and relative rates of sea-level rise for each patch using the station that was located in an area most similar to the patch; this was usually the nearest station and applied to the majority of patches. We used the mean of nearby stations to estimate values for a patch when no station existed in an area similar to the patch. For example, we recorded the mean sea level trend of Kings Point, Port Jefferson, and Montauk stations as the sea level trend for patches on Long Island's southern shore (Far Rockaway to Southampton, New York) where a long-term water level station is not present.



Figure 3. Examples of A) tidally restricted marsh (white arrows show individual restrictions), B) ditched marsh, and C) marsh treated with Open Marsh Water Management (OMWM).

Statistical Analyses

We conducted all analyses in a maximum likelihood framework in Program R (R Core Team 2014).

Overall Population Trends - We modeled population change for 19 of the SGCNs (Table 1) using generalized fixed-and mixed-effect models. We were not able to model trends for the remaining seven species due to very low total detections (Tricolored Heron, Yellow-crowned Night-Heron, Black Rail, Black-necked Stilt, Sedge Wren) or extreme clumping in our detections due to colonial breeding (Laughing Gull, Forster's Tern). In all analyses we only used data from survey points within the published species' range (Rodewald 2015) that overlapped with the Estuarine Intertidal Emergent Wetland patch layer of the NWI. The single exception to these rules was the coastal plain swamp sparrow, which is a tidal-marsh specialist occurring regularly in brackish marshes outside of the delineated patches from New Jersey south (Beadell et al. 2003).

For each of the 19 SGCNs, we modeled the sum of maximum detections at each survey point each year ("abundance index") within each tidal marsh patch (from the patch layer described in section IV above), using a negative binomial distribution and the *glm.nb* function within the "MASS" package (Venables and Ripley 2002). We included the fixed effects of year (as a continuous variable), patch area (logarithm transformed), the number of points visited within a patch each year (logarithm transformed), and the

number of visits to each patch per year (logarithm transformed). The parameter estimate for year in this model thus represents a relative index of population change within the surveyed region, controlling for the expected changes in detections due to the other fixed effects. For species with very low densities within 50 m or species with high detection probabilities that primarily use habitats on the upland marsh fringe (i.e., outside of areas where survey points were placed), we used counts from within 100 m of the survey point to increase model fit ($n = 10$; Table 15). This methodological change did require the use of a slightly different dataset than for species analyzed at the 50 m scale, although with similar spatial and temporal coverage across the region (Table 14).

As the historical data were both spatially and temporally heterogeneous in their sampling across the entire region, we also modeled population change for New England alone, considering time as a categorical variable with two levels (1998 – 2000 and 2011 – 2012). Our contemporary surveys and the historical surveys of T.P. Hodgman (MDIFW) and W.G. Shriver sampled all of New England adequately and employ identical methodology, making this smaller scale comparison particularly robust and an indirect method to validate the region-wide estimates.

For each of our five focal species (Clapper Rail, Willet, and , Nelson's, and Seaside sparrows), we modeled relative change in abundance at three additional spatial scales using the maximum count detected across all visits to a survey point each year as our response variable. We constructed Generalized Linear Mixed Models for each species with a Poisson distribution using the *glmer* function within the "lme4" package (Bates et al. 2014). As the historical data from different regions varied widely in temporal resolution (Table 14), we modeled change in maximum count at three different spatial scales: national wildlife refuge, state, and SHARP subregion.

At the refuge scale we modeled population change for each of four NWRs that spanned the full survey region (Rachel Carson, Parker River, Monomoy, and Bombay Hook NWRs), using survey year as a continuous, fixed effect. We used our knowledge of each refuge to build an appropriate random-effect structure specific to each model. All refuge models possessed a random effect for survey point identity, to control for repeated visits. For refuges with a variable number of visits to survey points per year (Rachel Carson and Parker River NWRs), we also included number of visits as a random effect. Lastly for Rachel Carson NWR, where the surveys spanned a large number of independent marsh patches across multiple watersheds, we also included patch area as a fixed effect. At the SHARP subregion and state scales we modeled maximum count using fixed effects for time (as the two-level categorical variable) and patch area. We included patch area to control for any changes in the mean size of patches surveyed by the different data sets through time. We also included three random effects. We used PSU to control for spatial autocorrelation at the scale of this sampling unit, and we included the number of visits to each survey point per year to control for differences in survey effort between points. Finally, we included categorical year to account for differences among years within each of the time steps. In effect, years become random, independent samples of either the earlier (1998 – 2000) or later (2011 – 2012) time periods. Trend estimates at the SHARP subregion and state scales were only estimated in New England due to historical data availability; historical data were much more sparse south of New England, preventing a robust analysis by state.

To assess whether there were statistically important changes in the populations of each species over either the categorical (early vs. late) or continuous time frames at each spatial scale, we compared the fully specified models above to a null model with the time variable removed using Akaike Information Criterion (AIC). We considered trends to be significant when the model including the variable for time improved model fit by a $\Delta AIC \geq 2.0$. We calculated 95% confidence intervals for all parameter estimates using the Wald approximation function.

To assess model fit and validate our estimate further, we (A) confirmed a dispersion ratio (Pearson residuals compared to degrees of freedom) between 0.33 and 3, (B) confirmed acceptable model fit using Q-Q plots of the random effect residuals, and (C) held out 30% of our data as a validation dataset to assess model accuracy for the two largest scale (New England and region-wide) analyses of the five focal species. Our parameter estimates come from analyses of the full dataset (training and validation dataset combined) after our model accuracy assessment.

In addition to parameter estimates, we estimate the linear annual percentage of population change for each model. We estimated compound annual change percentages using model estimates for the first and last year of survey ($[(\text{final}/\text{start})^{(1/\# \text{ years})} - 1]$). This approximates annual population change that is directly comparable across our various spatial, temporal, and metric scales as well as among species.

Marsh Modification Effects – We explored interactions between marsh modification and bird population change using AIC-based model selection for the five focal tidal-marsh specialists combined and for species-specific models for each of these five species. For each of these six model selections, we considered the performance of all combinations of four fixed effects: the interaction between ditching (at the 50 m radius scale) and year, the interaction between number of downstream restrictions and year, the interaction between local relative sea-level rise and year, and the interaction between the local 1% exceedance flooding values and year. Single additive terms were included whenever the interaction term was included, and all terms were scaled prior to analysis to allow for direct post-hoc comparison of parameter estimates. With no known exceptions, the overwhelming majority of marsh modifications occurred prior to our earliest survey data. Thus, each of these four interaction terms test whether more-modified marshes show different changes in bird populations through time compared to less-modified marshes. The extent of OMWM, while locally common, was highly restricted to only a few areas (i.e., New Jersey, Delaware, and Maryland), and we were therefore unable to test its effect across the entire region. We compared the performance of each of these models to a null model. Parameter weights were calculated by summing the set of AIC model weights that included each parameter.

All models, including the null, predicted maximum count per year at each surveyed point (with a Poisson link) as a function of two fixed effects. We included patch area (logarithm transformed) controlled for expected differences in maximum count in larger patches. The distance of a point upriver (logarithm transformed), measured as the straight-line distance to the coastline as defined by ArcGIS 10 state-outline basemaps (ESRI 2014), was included to account for differences from the impacts of storm surges and sea-level rise. All models also included the random effects of number of visits to the point for each year (to control for expected increases in maximum count with greater visitations) and PSU identity nested within NOAA gauge identity (to control for the pseudoreplication of NOAA gauge metrics across different points). The null structure of the multi-species models were identical to this structure except that we also included species as a random effect to control for variation across taxa.

We assessed model fit for all models similar to those for the raw trend estimates (above), including the use of dispersion ratios and Q-Q plots and by withholding 30% of our data for later validation. As with previous analyses, we report parameter estimates from the full dataset (training and validation datasets combined) after validating model accuracy. Parameter estimates are model-averaged across the models within 2.0 ΔAIC of the top-ranked model (Burnham and Anderson 2002). Further, to assess the sensitivity of the conclusions from the top-ranked multi-species model, we reran the model on an additional 31 datasets, where each dataset excluded a different section of the global dataset. To produce these additional datasets, we variously excluded each historical study, each species, one fifth of the latitudinal range, extremely modified points (those with >5 tidal restrictions), and 10 randomly selected groups of 10% of the data.

Table 15. Trend direction, percent annual change, parameter estimates for year ($\pm$ 95% confidence intervals), Δ AIC, and number of observations (n) for SGCN abundance indices within tidal marshes across USFWS Region 5.

Species	Survey radius (m)	Trend	% change/yr	β (95% CI)	Δ AIC	n
Least Bittern	100	.	.	-0.33 (-1.2, 0.49)	-1.39	403
Great Blue Heron	100	.	.	-0.09 (-0.25, 0.06)	-0.52	1535
Great Egret	100	(+)	6.1	0.26 (0.11, 0.41)	9.88	1205
Snowy Egret	100	.	.	-0.11 (-0.25, 0.02)	0.60	1535
Tricolored Heron	.	.	.	.	.	.
Little Blue Heron	100	.	.	-0.44 (-1.73, 0.81)	-1.53	1307
Black-crowned Night-Heron	50	.	.	0.32 (-0.24, 0.98)	-0.81	1550
Yellow-crowned Night-Heron	.	.	.	.	.	.
Glossy Ibis	100	(+)	11.6	0.49 (0.22, 0.76)	9.69	1366
American Black Duck	100	.	.	0.04 (-0.21, 0.29)	-1.90	1535
Clapper Rail	50	(-)	-4.6	-0.34 (-0.61, -0.06)	3.79	586
Virginia Rail	50	.	.	0.23 (-0.32, 0.88)	-1.39	1550
Black Rail	.	.	.	.	.	.
Black-necked Stilt	.	.	.	.	.	.
Willet	50	.	.	0.13 (-0.01, 0.27)	1.25	1550
Laughing Gull	.	.	.	.	.	.
Common Tern	100	.	.	0.02 (-0.32, 0.33)	-1.99	1535
Forster's Tern	.	.	.	.	.	.
Willow Flycatcher	100	.	.	0.22 (-0.07, 0.52)	0.25	1162
Sedge Wren	.	.	.	.	.	.
Marsh Wren	50	.	.	-0.07 (-0.33, 0.17)	-1.67	1289
Common Yellowthroat	100	(+)	8.5	0.38 (0.29, 0.47)	67.51	1535
Nelson's Sparrow	50	(-)	-4.2	-0.21 (-0.33, -0.08)	8.84	608
Saltmarsh Sparrow	50	(-)	-9.0	-0.43 (-0.56, -0.31)	44.08	1383
Seaside Sparrow	50	.	.	0.05 (-0.21, 0.3)	-1.86	809
Coastal Plain Swamp Sparrow	50	.	.	-0.06 (-0.2, 0.09)	-1.40	3691

¹ Trend directions are only reported when models with the term for time (a continuous term from 1994 – 2012) were Δ AIC $\leq$ 2.0 than models without this term. Abundance was modeled as the sum of observations across all visits to a tidal marsh patch, controlling for the number of visits to each patch and patch area.

Results

SGCN population trends

For the 19 SGCN species for which we modeled abundance over our 18-year period of observation (1994 – 2012) by tidal marsh patch, the abundance of six species was modeled better with a term for annual change than without one (ΔAIC range = 3.79 – 67.51; Table 15). Three species (great egret, glossy ibis, common yellowthroat) showed consistent increases over the period with mean annual increases of 6.5%, 11.6%, and 8.54%, respectively (Fig. 4). Three species (Clapper Rail, Nelson's sparrow, Saltmarsh Sparrow) showed consistent declines of 4.6%, 4.2%, and 9.0% respectively. The remaining 13 species appeared stable over the period of observation (Fig. 4). The two sparrow species that were declining across the region showed similar rates of decline within our more robust New England comparison across two time steps (Table 16). Glossy ibis and common yellowthroat also showed increases at this scale, but great egret and Clapper Rail were stable (Table 16).

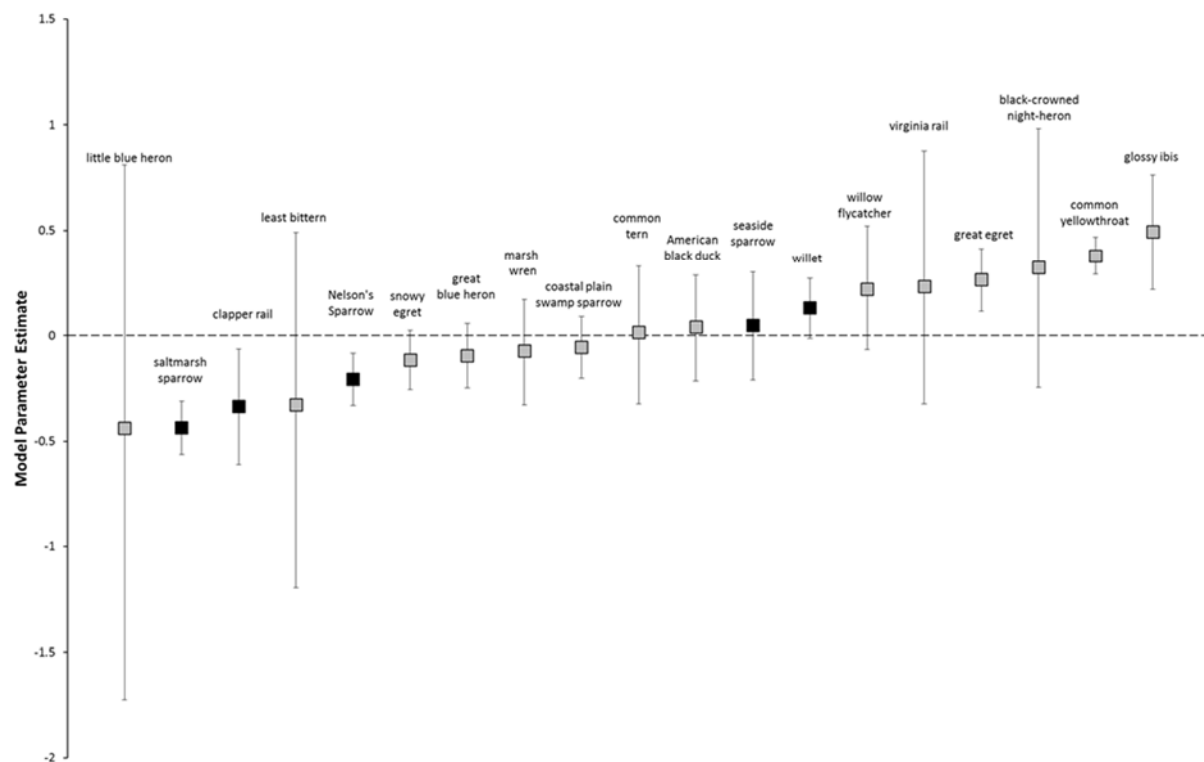


Figure 4. Estimates of the effect of year ($\pm$ 95% CI) on the summed maximum count per year per patch of each Species of Greatest Conservation Need (SGCN). Surveys were conducted between 1998 and 2012 in tidal marshes across USFWS Region 5. Black boxes indicate our five foc species.

Focal species population trends

Clapper Rail – When modeled by survey point instead of marsh patch (as above), Clapper Rail showed negative trends in our abundance index (modeled as maximum count at the point) at the refuge (Table 17), state (Table 18), and USFWS Region 5 (Table 19) scales. Across the entire region we estimate a 4.6% decline for this species per year.

Willet – Willet counts appeared stable at both the state (Table 18) and regional (Table 19) scales. Smaller

scale models showed mixed results (Table 17), with increases at Rachel Carson and Monomoy NWRs, a decrease at Bombay Hook NWR, and no detectable change at Parker River NWR.

Nelson's Sparrow – Nelson's sparrows showed decreases in abundance at both the New England (Table 18), and USFWS Region 5 scales (Table 19). Subregional models, however, lacked the statistical power to detect any change (Tables 18 and 19). There also appears to be heterogeneity in trends at the local scale, with Rachel Carson NWR showing an increase in abundance (Table 17), contrary to the estimates for that subregion (no change), state (no change), and the larger scale analyses (decrease). Across the entire region we estimated a 4.2% decline for this species per year.

Saltmarsh Sparrow – Saltmarsh sparrows showed declines in abundance index at the refuge (Table 17), state (Table 18), subregional, and regional scales (Table 19). Annual declines ranged from 5.0% (Rachel

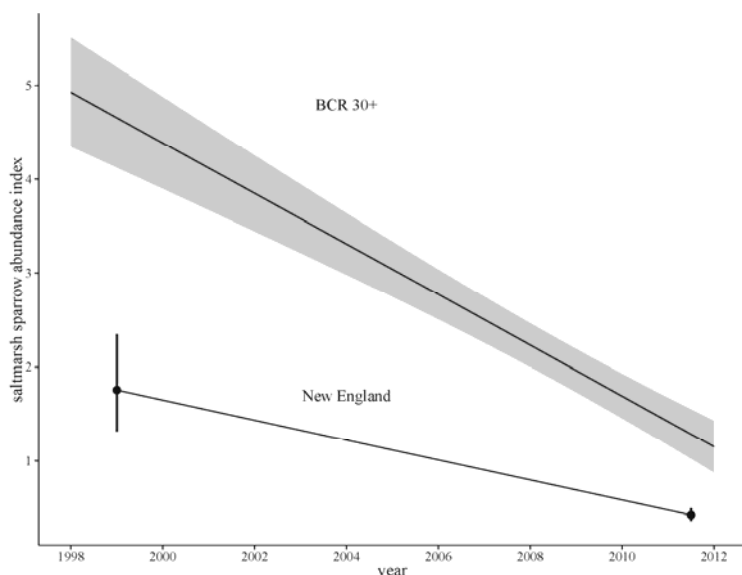


Figure 5. Estimates of the summed maximum count per year per patch of Saltmarsh Sparrows ($\pm$ 95% CI) by year for surveys conducted across USFWS Region 5 (BCR30+) and at two time points across New England, where surveys were conducted using the same field methods over the same spatial extent.

Carson NWR) to 18.5% (Coastal Maine). We detected significant declines in three of the four long-term refuge datasets (Rachel Carson, Parker River, and Bombay Hook NWRs), in two of the five New England states (Maine and Connecticut), in two of the three New England subregions (Coastal Maine and Cape Cod to Casco Bay), and across New England and USFWS Region 5 as a whole (Fig. 5). We detected no population increases at any scale, and parameter estimates for four of the five non-significant analyses were also negative. Across the entire region we estimate that Saltmarsh Sparrows experienced the greatest annual population change for any of our five focal species over our period of observation, a decline at the rate of 9.0% annually.

Seaside Sparrow – We detected no change in our abundance index for Seaside Sparrows for all scales except the refuge scale (Tables 17 – 19). Maximum yearly counts at Bombay Hook NWR (the only long-term refuge dataset with sufficient detections to model Seaside Sparrows) declined from 1994 to 2007 at a rate of 3.3% annually (Table 17). Across the entire region, we estimate that this species is stable (Table 19).

Our parameter estimates come from analyses of the full dataset (training and validation dataset combined) after our model accuracy assessment and model averaged parameter estimates are presented in Table 20.

Table 16. Trend direction, percent annual change, parameter estimates for year ($\pm$ 95% confidence intervals), Δ AIC, and number of observations (n) for SGCN abundance indices within New England tidal marshes.

Species	Survey radius (m)	Trend	% change/yr	β (95% CI)	Δ AIC	n
Least Bittern	100	.	.	.	.	.
Great Blue Heron	100	.	.	-0.41 (-0.83, 0.02)	1.50	1307
Great Egret	100	.	.	0.61 (0.12, 1.08)	3.91	980
Snowy Egret	100	.	.	-0.29 (-0.69, 0.09)	0.18	1307
Tricolored Heron	.	.	.	.	.	.
Little Blue Heron	100	.	.	-0.44 (-1.73, 0.81)	-1.53	1307
Black-crowned Night-Heron	50	.	.	0.39 (-0.98, 1.93)	-1.70	1307
Yellow-crowned Night-Heron	.	.	.	.	.	.
Glossy Ibis	100	(+)	9.0	0.95 (0.14, 1.72)	3.14	1138
American Black Duck	100	.	.	-0.18 (-0.97, 0.55)	-1.78	1307
Clapper Rail	50	.	.	-0.39 (-1.29, 0.53)	-1.31	516
Virginia Rail	50	.	.	1.27 (-0.64, 4.31)	-0.51	1307
Black Rail	.	.	.	.	.	.
Black-necked Stilt	.	.	.	.	.	.
Willet	50	.	.	0.09 (-0.3, 0.46)	0.65	1307
Laughing Gull	.	.	.	.	.	.
Common Tern	100	.	.	0.33 (-0.71, 1.23)	-1.56	1307
Forster's Tern	.	.	.	.	.	.
Willow Flycatcher	100	.	.	0.44 (-0.54, 1.46)	-1.23	960
Sedge Wren	.	.	.	.	.	.
Marsh Wren	50	.	.	-0.39 (-1.11, 0.28)	-0.71	1111
Common Yellowthroat	100	(+)	6.9	0.74 (0.48, 1.00)	28.52	1307
Nelson's Sparrow	50	(-)	-5.9	-0.67 (-1.09, -0.26)	8.28	448
Saltmarsh Sparrow	50	(-)	-12.2	-1.22 (-1.57, -0.89)	49.68	1138
Seaside Sparrow	50	.	.	0.23 (-0.5, 0.95)	-1.62	734
Coastal Plain Swamp Sparrow	.	.	.	.	.	.

¹ Trend directions are only reported when models with term for time (a categorical term for early – 1998-2000 – versus late – 2010-2012) were Δ AIC $\leq$ 2.0 than models without this term. Abundance modeled as sum of observations across all visits to a tidal marsh patch, controlling for the number of visits to each patch and patch area.

Table 17. Estimated annual population change¹ and parameter estimates (β and 95% confidence intervals) for five tidal marsh specialists from long-term surveys at four National Wildlife Refuges (NWR).

Refuge	<i>Clapper Rail</i>		<i>Willet</i>		<i>Nelson's Sparrow</i>		<i>Saltmarsh Sparrow</i>		<i>Seaside Sparrow</i>	
	Annual change	β (95% CI)	Annual change	β (95% CI)	Annual change	β (95% CI)	Annual change	β (95% CI)	Annual change	β (95% CI)
Rachel Carson NWR (2000 - 2012)	- out of species range -		7.1% ²	0.25 (0.12, 0.39)	4.1%	0.15 (0.02, 0.28)	-5.0%	-0.19 (-0.33, -0.05)	- out of species range -	
Parker River NWR (2000 - 2012)	- out of species range -		.	0.03 (-0.11, 0.15)	- out of species range -		-5.6%	-0.22 (-0.32, -0.11)	- out of species range -	
Monomoy NWR (2005 - 2012)	- out of species range -		10.8%	0.24 (0.04, 0.43)	- out of species range -		.	-0.12 (-0.3, 0.05)	- out of species range -	
Bombay Hook NWR (1994 - 2007)	-18.1%	-0.8 (-0.97, -0.64)	-12.7%	-0.55 (-0.64, -0.45)	- out of species range -		-9.5%	-0.4 (-0.67, -0.14)	-3.3%	-0.14 (-0.19, -0.08)

¹ Trend directions are only reported when models with the term for time were $\Delta AIC \leq 2.0$ than models without this term.

² Bold values indicate parameter estimates where the 95% confidence intervals do not overlap zero.

Table 18. Estimated annual population change¹ and parameter estimates (β and 95% confidence intervals) for five tidal marsh specialists within five states with sufficient historical data.

State	<i>Clapper Rail</i>		<i>Willet</i>		<i>Nelson's Sparrow</i>		<i>Saltmarsh Sparrow</i>		<i>Seaside Sparrow</i>	
	Annual change	β (95% CI)	Annual change	β (95% CI)	Annual change	β (95% CI)	Annual change	β (95% CI)	Annual change	β (95% CI)
Maine	- out of species range -		- data too sparse -		.	-0.26 (-0.66, 0.13)	-10.6%	-1.23² (-1.63, -0.82)	- out of species range -	
New Hampshire	- out of species range -		- data too sparse -		- data too sparse -		.	-1.29 (-2.93, 0.35)	- out of species range -	
Massachusetts	- out of species range -		.	0.07 (-0.48, 0.62)	- data too sparse -		.	-0.22 (-0.63, 0.2)	- out of species range -	
Rhode Island	- out of species range -		.	-2.22 (-5.83, 1.4)	- out of species range -		.	0.5 (-0.27, 0.95)	.	-0.49 (-2.06, 1.09)
Connecticut	-12.9%	-1.65 (-2.29, -1.02)	.	-0.42 (-0.83, -0.01)	- out of species range -		-9.5%	-1.1 (-1.46, -0.73)	.	-0.26 (-0.75, 0.23)

¹ Trend directions are only reported when models with term for time (a categorical term for early – 1998-2000 – versus late – 2010-2012) were $\Delta AIC \leq 2.0$ than models without this term.

² Bold values indicate parameter estimates where the 95% confidence intervals do not overlap zero.

Table 19. Estimated annual population change¹ and parameter estimates (β and 95% confidence intervals) for five tidal marsh specialists within four subregions across USFWS Region 5 with sufficient data for analysis.

Subregion	<i>Clapper Rail</i>		<i>Willet</i>		<i>Nelson's Sparrow</i>		<i>Saltmarsh Sparrow</i>		<i>Seaside Sparrow</i>	
	Annual change	β (95% CI)	Annual change	β (95% CI)	Annual change	β (95% CI)	Annual change	β (95% CI)	Annual change	β (95% CI)
Coastal Maine ²	- out of species range -		- data too sparse -		·	0.04 (-0.18, 0.27)	-18.5%	-2.25³ (-3.55, -0.94)	- out of species range -	
Cape Cod to Casco Bay ²	- out of species range -		·	0.31 (-0.45, 1.06)	·	-0.53 (-0.95, -0.12)	-7.3%	-0.86 (-1.29, -0.37)	- out of species range -	
Southern New England ²	- data too sparse -		·	-1.34 (-2.66, -0.02)	- out of species range -		·	-0.41 (-0.73, -0.1)	·	-0.31 (-0.78, 0.16)
New England ⁴	·	0.41 (-1.29, 0.53)	·	0.09 (-0.3, 0.46)	-5.9%	-0.67 (-1.09, -0.26)	-4.2%	-1.22 (-1.57, -0.89)	·	0.23 (-0.5, 0.95)
FWS Region 5 (1998 - 2012) ⁴	-4.6%	-0.34 (-0.61, -0.06)	·	0.13 (-0.01, 0.27)	-4.2%	-0.21 (-0.33, -0.08)	-9.0%	-0.43 (-0.56, -0.31)	·	0.05 (-0.21, 0.3)

¹Trend directions are only reported when models with term for time that were $\Delta AIC \leq 2.0$ than models without this term.

²Early vs. late temporal analysis (11-year gap)

³Bold values indicate parameter estimates where the 95% confidence intervals do not overlap zero.

⁴Time modeled as continuous variation in year

Table 20. Model-averaged parameter estimates¹ (95% confidence intervals) for top-ranked models ($\Delta AIC \leq 2.0$) of tidal marshbird abundance (i.e., maximum counts per year at a survey point) for five focal species in USFWS Region 5.

Species	Marsh ditching X Year	Tidal restriction X Year	Sea-level rise trend X Year	1% Exceedance value X Year	<i>n</i>
Clapper Rail	0.06 (-0.03, 0.35)	0.03 (-0.25, 0.31)	0.01 (-0.23, 0.37)	-0.2 (-0.23, 0.37)	2161
Willet	-0.05 (-0.08, -0.01)²	0 (-0.1, 0.1)	-0.25 (-0.35, -0.15)	.	5501
Nelson's Sparrow	0.05 (-0.02, 0.12)	0 (-0.11, 0.1)	0.02 (-0.03, 0.06)	0 (-0.04, 0.06)	2393
Saltmarsh Sparrow	. ³	-0.25 (-0.34, -0.16)	0.04 (-0.09, 0.17)	0.04 (0.02, 0.1)	5180
Seaside Sparrow	.	0.33 (-0.02, 0.68)	0.05 (0.02, 0.32)	-0.11 (-0.27, -0.04)	2577
All focal species	-0.01 (-0.04, 0)	-0.16 (-0.21, -0.11)	-0.09 (-0.15, -0.03)	.	17812

¹ All data were scaled prior to analyses to allow for direct comparison of parameter estimates.

² Bold values indicate parameter estimates where the 95% confidence intervals do not overlap zero.

³ Blank values indicate that the parameter was not included in the top model(s).

Marsh Modification Effects

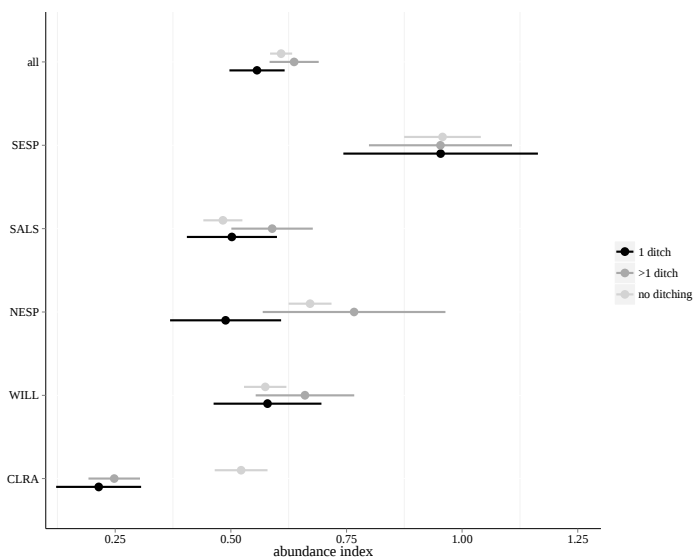


Figure 6. Parameter estimates ($\pm$ 95% CI) for the effect of marsh ditching on an index of tidal marsh bird abundance (the maximum count at a survey point over multiple visits each breeding season). SESP = Seaside Sparrow; SALS = Saltmarsh Sparrow; NESP = Nelson's sparrow; WILL = Willet; CLRA = Clapper Rail

Marsh modification was widespread across all states and subregions (Table 21). We detected marsh ditching within 100 meters of 35.1% of our contemporary (2011 – 2012) survey points. We detected at least one tidal restriction downriver of 42.6% of our survey points. We found OMWM treatments at a lower proportion of points (4.8%) across USFWS Region 5. These points, however, were concentrated mainly in Delaware (12.7% of points), Maryland (12.0%) and New Jersey (12.8%). Due to their local distribution, we did not include OMWM in any of candidate models during model selection.

Marsh ditching – The interaction

between marsh ditching (within 50 m of the survey point) and time was in the top model for three of the five focal species and the overall model with all five focal species combined (Table 20). The interaction term for ditching, however, was not significant in all but the Willet and the community models, where the effects on trends were unclear (e.g., greatest declines with intermediate ditching).

For the full community analysis, there was a 56.9% probability (parameter weight) that the effect of ditching on population trends was in the best model among the candidate model set. The parameter weight for ditching among the single-species models ranged from 12.9% (Seaside Sparrow) to 86.3% (Nelson's sparrow) with a mean ($\pm$ SD) of 48.0% ($\pm$ 31.3%). The ditching interaction term alone, however, was ranked lower than the null model in all six model selections. Abundance also did not appear to be strongly impacted by the degree of ditching, with the exception of Clapper Rails, for which abundance was significantly higher in unditched marshes (Fig. 6).

Table 21. Extent of tidal marsh modification by state across USFWS Region 5 as of 2014.

State	Marsh ditching		Open Water Marsh Management (OMWM)		Percent locations affected by downriver tidal restriction	Total locations ¹
	Percent locations affected (50m)	Percent locations affected (100m)	Percent locations affected (50m)	Percent locations affected (100m)		
Maine	9.43	13.52	0.00	0.00	58.18	318
New Hampshire	41.94	50.00	0.00	0.00	67.74	62
Massachusetts	60.31	66.54	0.00	0.00	44.36	257
Rhode Island	33.33	46.30	0.00	0.00	72.22	54
Connecticut	66.33	74.49	0.00	0.00	47.96	98
New York	55.38	64.62	0.77	0.77	43.85	130
New Jersey	40.86	49.14	9.14	12.86	49.14	350
Delaware	38.24	49.02	6.86	12.75	28.43	102
Maryland	38.39	47.32	6.25	12.05	27.68	224
Virginia	0.47	0.47	0.00	0.00	11.16	215
Total (Region 5)	35.08	41.77	2.98	4.75	42.60	1810

¹ Locations where modifications were measured (i.e., bird survey points) were stratified by land ownership and ecological subregion

Tidal restrictions – The interaction between the number of tidal restrictions (downstream of the survey point) and time was included in the top models for each of the five species and the community-level analysis, although it was only significant for the community wide model and for Saltmarsh Sparrows (Table 20). In the community-level analysis, the abundance index was stable over the period of observation in unrestricted marshes but declined in restricted marshes (Fig. 7). Declines were evidenced for both restricted and unrestricted marshes for Saltmarsh Sparrows, although declines were steeper in restricted marshes (Fig. 8). Models that included the interaction between tidal restriction and abundance index trends were ranked higher than all models that did not (including the null) for the community model (restriction interaction parameter weight > 99.9%) and all of the single-species models (parameters weights all > 99.9%) except for Clapper Rail (parameter weight = 95.3%), where the first ranked model without the restriction interaction was still 6.0 Δ AIC from the top-ranked model. Tidal restriction also impacted abundance on average at marshes, controlling for temporal trends (Fig. 9).

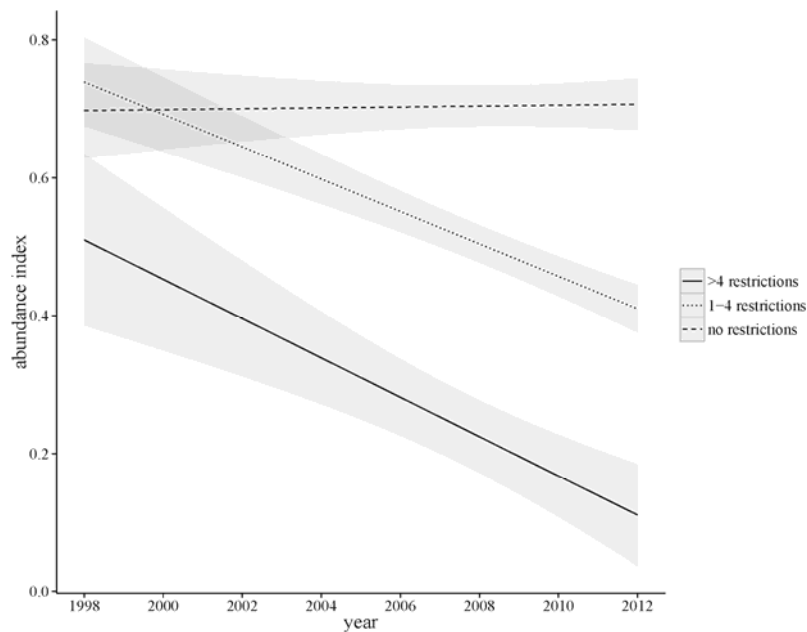


Figure 7. Effect of tidal restrictions on the maximum count at a survey point over time in all five focal species for the USFWS Region 5, Model output accounts for patch area, distance upriver, species, number of visits per point per year, and spatial autocorrelation among points.

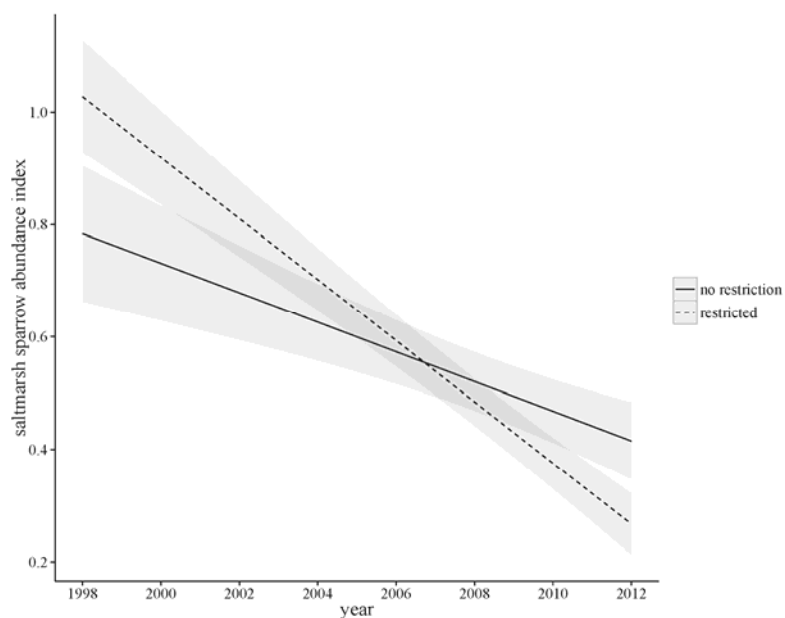


Figure 8. The predicted mean maximum count of Saltmarsh Sparrows per point ($\pm$ 95% CI) for each year in tidal marshes across USFWS Region 5 in marshes with tidal restrictions downriver of the survey point (dotted line) and those without restriction (solid line).

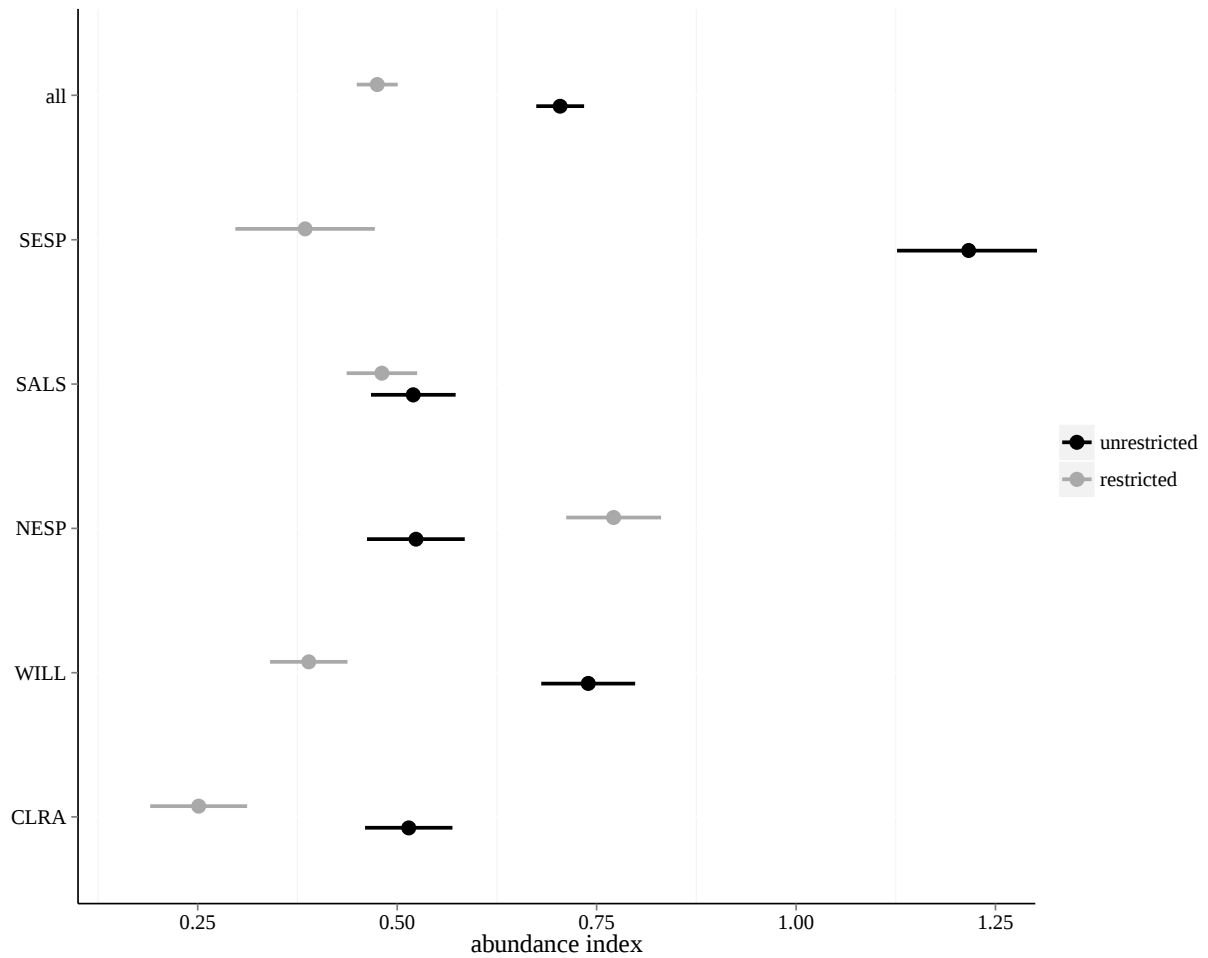


Figure 9. Parameter estimates ($\pm$ 95% CI) for the effect of tidal restriction downstream of a survey point on an index of tidal marsh bird abundance (the maximum count at the point over multiple visits each breeding season). SESP = Seaside Sparrow; SALS = Saltmarsh Sparrow; NESP = nelson's sparrow; WILL = Willett, and CLRA = Clapper Rail.

Sea-level rise – Local trends for relative sea-level rise were also important predictors of changes in bird counts during our observation periods. The interaction term between sea-level rise and time was in the top models for all five, single-species analyses and in the focal-species community analysis (Table 20). The parameter weight for the community model was 95.6%. Among the single-species analyses, parameters weights were 24.8% (Clapper Rail), 34.1% (Seaside Sparrow), 80.6% (Saltmarsh Sparrow), 88.4% (Nelson’s sparrow), and > 99.9% (Willet). The effect of sea-level rise on the population trend was variable by both year and species (Fig. 10). The same was true for the effect of sea-level rise on abundance (Fig. 11). The rate of sea-level rise, however, is strongly correlated with latitude, and finer scale analyses would be required before we could eliminate position within the range as an alternative explanation of these patterns.

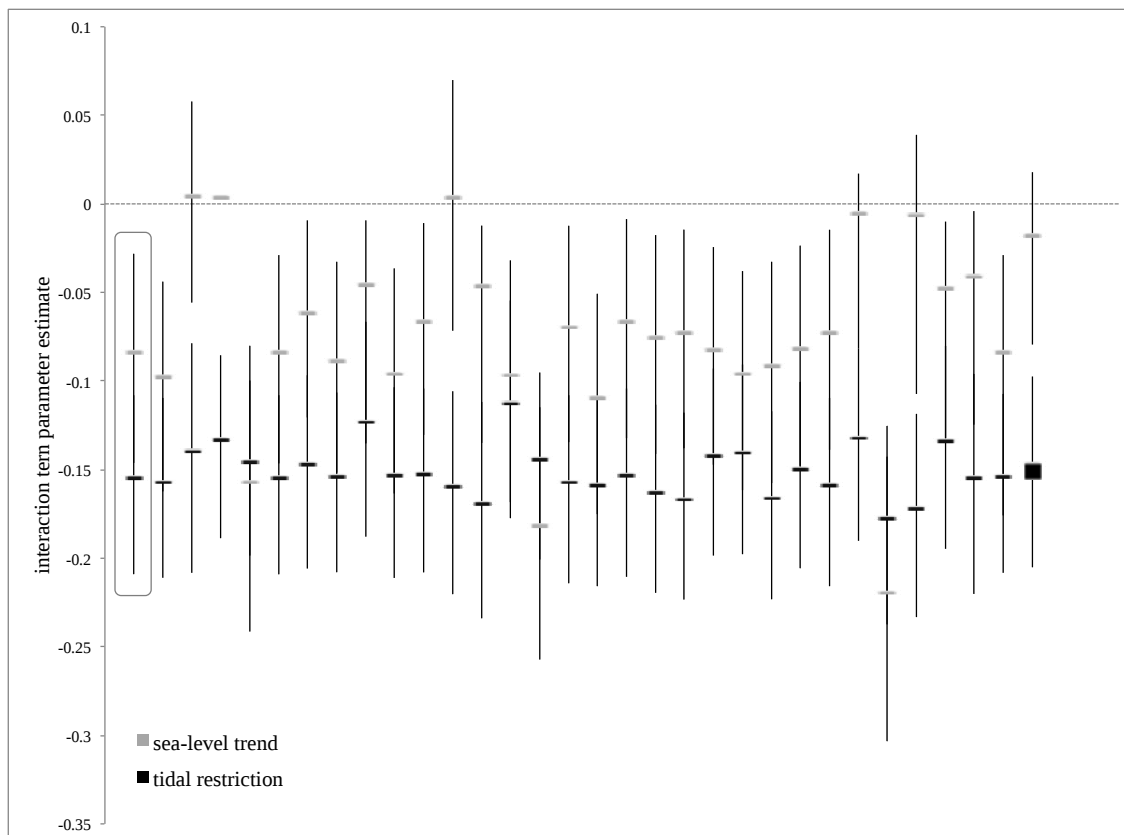


Figure 10. Parameter estimates ($\pm$ 95% CI) for the interaction between time (year) and either the number of tidal restrictions downriver of a marsh or the 30-year average sea-level rise trend (measured by nearby NOAA buoy data). The complete model predicts the maximum number of birds detected for five tidal-marsh specialist species (Willet, Clapper Rail, and Nelson’s , and Seaside sparrows), controlling for patch area, distance upriver, species identity, and the number of visits to the survey point each year. Each point (n=31) represents a different subset of our complete dataset to test the stability of the parameter estimates. Parameter estimates from the complete dataset is shown in the box.

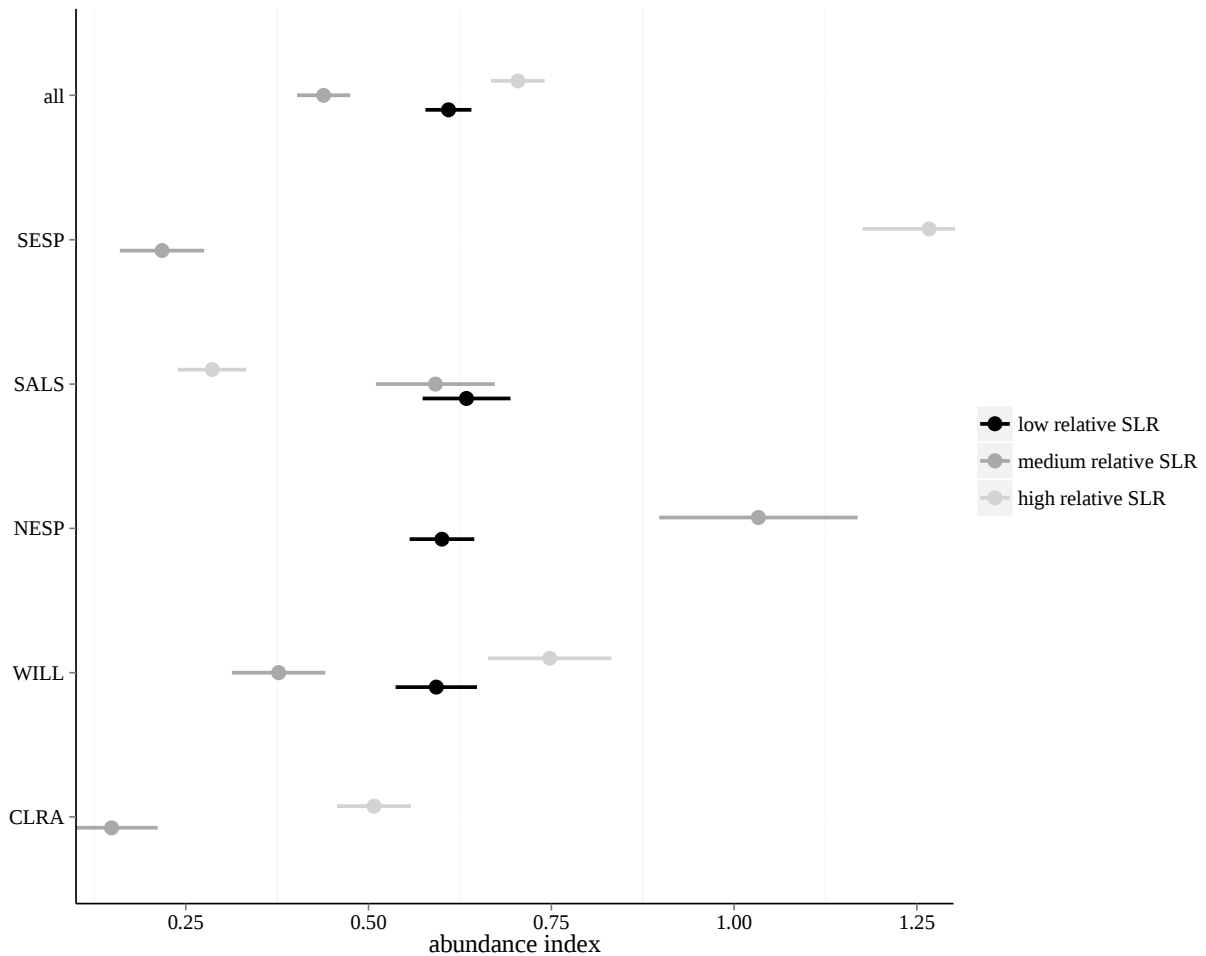


Figure 11. Parameter estimates ($\pm$ 95% CI) for the effect of local rate of relative sea-level rise on an index of tidal marsh bird abundance (the maximum count at the point over multiple visits each breeding season). SESP = Seaside Sparrow; SALS = Saltmarsh Sparrow; NESP = nelson's sparrow; WILL = Willett, and CLRA = Clapper Rail.

High-marsh flooding probability – The frequency of flooding of the marsh surface (as indicated by 30-year mean, 1% exceedance values) was not included in the top models for the entire community (parameter weight = 16.5%) or for the model for Willett (weight = 12.5%). Further they were not significant for the models for either Clapper Rail (weight = 88.8%) or Nelson's sparrow (weight = 31.6%). For Saltmarsh Sparrows (weight = 93.0%), declines were steepest in marshes with more frequent flooding (those with exceedance values in the top third), and declines were similar among marshes in the bottom two-thirds of exceedance values. Conversely, Seaside Sparrows (weight = 67.4%) increased in marshes with exceedance values in either the bottom or top third of values, but declined in marshes with intermediate exceedance values. Like sea-level rise, however, exceedance values are correlated with latitude, with the highest values in the Long Island Sound and declines toward both the north and south. Finer scale analyses would be necessary to eliminate this spatial pattern as the cause for these effects.

Tidal restriction versus sea-level rise – While the effects of both tidal restriction and relative rate of sea-level rise were in the top models for all five species and the community model, the relative importance of the two drivers of population change varied. For the community model using the full

dataset, the effect of tidal restriction on population decline was greater than relative sea-level rise (Fig. 10). This ranked importance was stable across all regions and species (Fig. 10). Further the predicted effect of restriction on population trend was very consistent, but the effect of local sea-level rise was more variable (Fig. 10). It is clear, however, that both drivers are important for predicting changes in populations through time. Models with both interaction terms ranked higher than models with just a single interaction for all but the model for Seaside Sparrows, where restriction and exceedance values were most important.

Conclusions

In coastal marshes of the northeast, tidal restriction drives declines both in the Saltmarsh Sparrow (Fig. 8) and in the specialist avifaunal community as a whole (Fig. 7), and it supersedes relative sea-level rise as a dominant driver of community decline (Fig. 10). On average, tidal-marsh specialists are declining in locations that are tidally restricted, but are maintaining their populations in marshes that have no road crossings affecting tidal flow. Anthropogenic modification of marshes directly affects soil chemistry and sediment supply to coastal wetlands (Portnoy and Giblin 1997a,b), which in turn affect vegetative communities in these areas (Warren and Niering 1993). Marsh accretion, driven both by sediment input and accumulation of dead vegetative material as peat, is the primary mechanism available to coastal marshes to keep pace with local and regional sea-level rise (Pont et al. 2002; Day et al. 1997). In short, marshes need sediment to maintain high marsh communities with sea-level rise, and tidal restrictions starve marshes of sediment supply.

The relative success of Monomoy NWR at maintaining tidal marsh bird populations may serve as an appropriate object lesson due its geomorphological and human impact conditions. The refuge consists of a semi-open beach system, where overwash from the beach can supply sediment to the marsh. This refuge was the only area where we detected no declines in any tidal marsh species. Conversely, Bombay Hook NWR shows the steepest declines for all tidal-marsh specialists and is more restricted, although only upriver from the majority of the marsh. The relative rate of sea-level rise is higher in the Mid-Atlantic than it is in New England, and that may explain much of the challenges to more southern systems. Sea-level rise alone does not explain population declines, however, and for those areas with higher rates of sea-level rise, a ready sediment supply is likely even more important for maintaining high marsh habitats and the organisms they support.

The steepest significant decline detected was in the Saltmarsh Sparrow (Fig. 4), the species most specialized to high marsh. Unlike other specialists, the Saltmarsh Sparrow exists completely in coastal marshes of the eastern United States, and utilizes only the high-marsh zone for nesting and raising young (Greenlaw and Rising 1994; Shriver et al. 2010). With no known alternate refugia for this species, the negative trends we found at every spatial scale are alarming but not surprising. In light of sea-level rise and declining sediment supplies from marsh restriction, the global population of the Saltmarsh Sparrow will continue to shrink with declining high marsh extent. We found similar declines both locally and across the region for the Clapper Rail, which also nests exclusively in the high marsh. The species did appear stable in New England, although it is uncommon there overall.

The Seaside Sparrow is similar to the Saltmarsh Sparrow in that it also exists exclusively in tidal marshes of the eastern United States, however its breeding range is much larger, encompassing much of western Florida and the Gulf coast (Post and Greenlaw 2009). The only significant trend observed for this species was at Bombay Hook NWR, a refuge that produced negative trends in all species examined. The

difference in trend between this species likely reflects the Seaside Sparrow's broader selection of microhabitat for breeding within tidal marsh, which is inclusive of the wetter low-marsh zone (Kern 2015; Pennings and Callaway 1992). This combined with the more expansive breeding range of this species may be important in maintaining Seaside Sparrow breeding populations within northeastern tidal marshes.

We found no regional trends for Willets, despite them occurring across the entirety of USFWS Region 5. Instead we found heterogeneous trends at the local level, with three of the four refuges showing significant trends in both directions. There is no emergent story for eastern Willet, although it appears that prevailing population drivers exist at the local level. In contrast to our other tidal marsh specialists, however, Willets do not nest exclusively in the marsh, also using coastal dune grass systems. The heterogeneity in local population change we report here may reflect the local availability of alternative nesting substrates.

VI. Fecundity

Methods

Nest monitoring & nest success

From 2011 to 2013, we implemented a standardized data collection protocol (Appendix B) for our five focal species plus American black duck at twenty-three study plots (Table 22) spanning a great circle distance of approximately 575 km (Fig. 12). Our survey covered 59% of the Saltmarsh Sparrow's breeding range (based on distribution data reported in section IV, above) and 89% of the breeding range of the nominate subspecies, *Ammodramus caudacutus caudacutus* (Montagna, 1942). Study plots consisted of

1-28 ha areas of tidal marsh in the high-marsh zone. At each study plot, we searched for nests at least once per week throughout the breeding season (May to August). Once we found a nest, we revisited it every 2-4 days (with rare exceptions) to determine success or failure. If a nest failed, we determined the cause of nest failure based on evidence at the nest site (Appendix B).

Broadly, we assigned depredation as the cause of nest failure to nests found with broken or punctured eggs, mangled chicks, or to nests that were empty and dry after nights that did not have tides high enough to flood the high marsh. We assigned flooding as the cause of failure to nests that were wet after nights with tides high enough to inundate the high marsh, contained drowned chicks, or had intact eggs outside the nest (presumably because they floated out). We classified nests as failed for unknown reasons in cases of conflicting evidence (e.g., nest bowl was visibly wet and contained punctured eggs). We considered nests successful if, after survival on all previous visits, they were found empty when at least one nestling would have been 10 days old, the age at which chicks are able to leave the nest (Greenlaw & Rising, 1994).

We captured females at nests with mist nets and individually marked them with uniquely-numbered aluminum leg bands (United States Geological Survey) to track multiple breeding attempts within the same season (see Seasonal Fecundity, below). In part of their range,

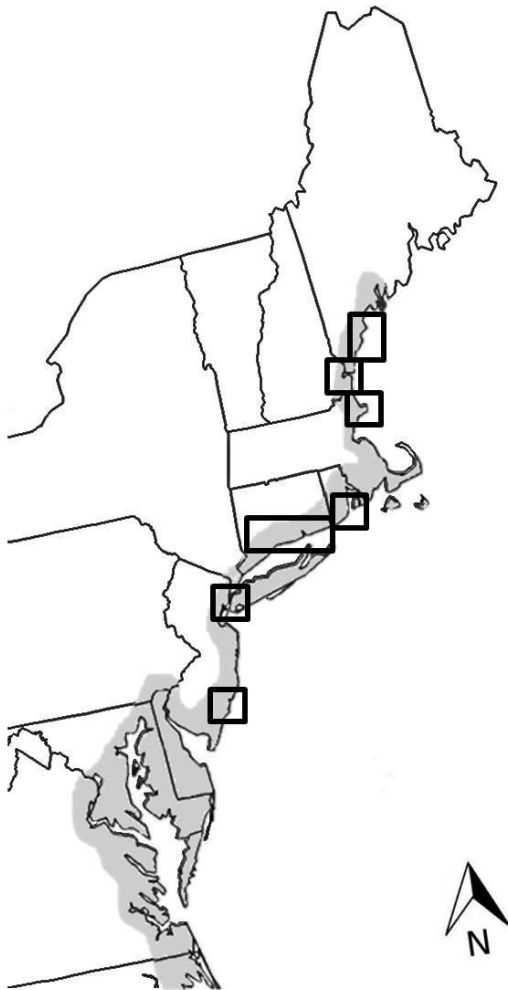


Figure 12. Our demographic study plots span seven states within the Saltmarsh Sparrow breeding range (shaded). Within each boxed area, we surveyed one to five study plots (generally in different watersheds) for a total of 23 plots.

Saltmarsh Sparrows are sympatric and interbreed with their sister species, the Nelson's sparrow. Within this hybrid zone (Gulf of Maine), we only identified a nest as belonging to either species if we successfully caught the female, whereas outside of the hybrid zone (Long Island Sound and south), species identity was assigned by egg and nest characteristics. Species identity within the hybrid zone was assigned using a linear discriminant function analysis developed with to predict the genetic species identity (separating pure and back-crossed Saltmarsh Sparrows from pure and back-crossed Nelson's sparrows) using morphometric and plumage characteristics (Walsh et al. 2015). First and second generation hybrids (F1 & F2) are exceedingly rare in this hybrid zone (measured at our study plots: Walsh et al. 2015).

We used the program MCestimate (Etterson et al., 2007, 2014) to calculate daily probabilities of nest survival and failure from competing risks. MCestimate employs a Markov chain algorithm to estimate daily nest-failure probabilities via a generalization of the Mayfield method (Mayfield, 1975). Unlike more traditional logistical exposure models (Dinsmore et al., 2002; Rotella et al., 2004; Shaffer, 2004), MCestimate can separately estimates probabilities of failure due to competing risks, in addition to total daily nest survival probability. To report the daily probabilities of nest depredation, nest flooding, and total nest survival by study plot, we created models with study plot as the sole fixed-effect covariate to allow for maximum variation. We only calculated cause-specific failure probabilities, however, for the species for which we had the most data (Saltmarsh Sparrow). For the remaining species we estimated failure risk as a single daily probability.

We also report annual nest abundance (total nests found during each breeding season) and nest density (nest abundance divided by plot area) for all six species by study plot. To capture relative effort at each of these areas, we present the date of the first-laid egg (either observed, or back-calculated from hatching dates) and the date of the first-laid egg in the last observed nest across all six species on each study plot. Nests were observed for up to 25 days after this first-laid egg, depending on nest outcome.

Seasonal Fecundity

For the three species where we individually marked females (Seaside, , and Nelson's sparrows), we used the program MCnest to estimate average seasonal fecundity of females via population projections at each study plot (Saltmarsh Sparrow) or US State (Seaside and Nelson's sparrows). For full details on MCnest, see Bennett and Etterson (2007) as well as Etterson and Bennett (2013). In short, MCnest creates a compound Markov chain, composed of time-varying transition probabilities from one state to another based on daily nest failure probabilities (calculated in MCestimate, as above) and various life history parameters. We modeled female transitions among seven states: pre-breeding, rapid follicle growth, egg laying, incubation, nestling brooding, waiting to renest following a failed nesting attempt, waiting to renest following a successful attempt, and post-breeding. The compound Markov chain ultimately describes the probabilities of every transition from one state to another for each day of the breeding season. Projections then simulate females within this Markov chain and calculate the expected number of successful broods per season for each simulated female. We estimated fecundity for each study plot or US State by multiplying this value by the mean successful brood size for each species (brood size did not vary significantly among study plots for any of the three sparrows). For each projection, we modeled a population of 100 females to estimate seasonal fecundity and its variance.

We parameterized the length of each state using either field data or values from the literature. We included observed spatial variation in these parameters whenever appropriate. For each parameter, we first identified if the trait varied locally by testing for differences in mean trait values across study plots

Table 22. Location and associated covariate information for 23 plots for the study of tidal marsh bird reproduction, 2011-2013.

Study Plot	State	Latitude (decimal degrees)	Longitude (decimal degrees)	Nearest Observed Water Level Station	Maximum High Tide May-Aug, 2011-2013 (meters)	Nearest Observed Exceedance Level Station	1% Exceedance Probability Value (meters)	Nearest sea level rise location (Boon et al. 2012)	Sea level rise probability 1969-2011 (millimeters)	Patch area (hectares)
Oyster Creek	NJ	39.5	-74.4	Atlantic City, NJ	1.60	Atlantic City, NJ	1.47	Atlantic City, NJ	4.63	5807.2
Mullica Wilderness	NJ	39.5	-74.4	Atlantic City, NJ	1.60	Atlantic City, NJ	1.47	Atlantic City, NJ	4.63	5807.2
AT&T	NJ	39.7	-74.2	Atlantic City, NJ	1.60	Atlantic City, NJ	1.47	Atlantic City, NJ	4.63	2174.6
Four Sparrow Marsh ¹	NY	40.6	-73.9	Sandy Hook, NJ	1.64	Sandy Hook, NJ	2.06	Sandy Hook, NJ	4.19	16.8
Sawmill Creek ¹	NY	40.6	-74.2	Bergen Pt., West Reach, NY	1.65	The Battery, NY	1.68	The Battery, NY	3.47	87.5
Marine Nature Park ¹	NY	40.6	-73.6	Sandy Hook, NJ	1.64	Sandy Hook, NJ	2.06	Sandy Hook, NJ	4.19	16.9
Idlewild ¹	NY	40.7	-73.8	Sandy Hook, NJ	1.64	Sandy Hook, NJ	2.06	Sandy Hook, NJ	4.19	94.7
East River	CT	41.3	-72.7	New Haven, CT	2.50	Bridgeport, CT	1.65	New London, CT	3.53	436.8
Hammonasset	CT	41.3	-72.5	New Haven, CT	2.50	New London, CT	1.89	New London, CT	3.53	244.7
Pattagansett	CT	41.3	-72.2	New London, CT	1.50	New London, CT	1.89	New London, CT	3.53	25.8
Waterford	CT	41.3	-72.1	New London, CT	1.50	New London, CT	1.89	New London, CT	3.53	8.1
Barn Island	CT	41.3	-71.9	New London, CT	1.50	New London, CT	1.89	New London, CT	3.53	134.3
John H. Chaffee	RI	41.4	-71.5	Newport, RI	1.44	Newport, RI	1.84	New London, CT	3.53	73.5
Sachuest Point	RI	41.5	-71.2	Newport, RI	1.44	Newport, RI	1.84	New London, CT	3.53	20.0
Parker River	MA	42.8	-70.8	Fort Point, NH	2.27	Seavey Island, ME	1.14	Boston, MA	2.88	1322.2
Chapman's Landing	NH	43.0	-70.9	Fort Point, NH	2.27	Seavey Island, ME	1.14	Portland, ME	0.94	69.7
Lubberland Creek	NH	43.1	-70.9	Fort Point, NH	2.27	Seavey Island, ME	1.14	Portland, ME	0.94	22.4
Eldridge Road	ME	43.3	-70.6	Wells, ME	2.41	Seavey Island, ME	1.14	Portland, ME	0.94	381.2

Table 22. Continued.

Study Plot	State	Latitude (decimal degrees)	Longitude (decimal degrees)	Nearest Observed Water Level Station	Maximum High Tide May-Aug, 2011-2013 (meters)	Nearest Observed Exceedance Level Station	1% Exceedance Probability Value (meters)	Nearest sea level rise location (Boon et al. 2012)	Sea level rise probability 1969-2011 (millimeters)	Patch area (hectares)
Little River	ME	43.3	-70.5	Wells, ME	2.41	Seavey Island, ME	1.14	Portland, ME	0.94	86.4
Jones Creek	ME	43.5	-70.4	Portland, ME	2.46	Portland, ME	1.23	Portland, ME	0.94	888.5
Nonesuch River	ME	43.6	-70.3	Portland, ME	2.46	Portland, ME	1.23	Portland, ME	0.94	888.5
Libby River	ME	43.6	-70.3	Portland, ME	2.46	Portland, ME	1.23	Portland, ME	0.94	888.5
Scarborough River	ME	43.6	-70.4	Portland, ME	2.46	Portland, ME	1.23	Portland, ME	0.94	888.5

¹ Water level values were obtained from 2012 and 2013 data only because this study plot was not surveyed in 2011 when Hurricane Irene resulted in particularly high water levels in this area.

(or US states in the case of Nelson's and Seaside sparrows). For parameters that did not vary significantly by study plot or for which we had too little data to test for differences among study plots, we used either a value from the literature or the global mean trait value across all study plots. For parameters that varied significantly by study plot, we used the mean trait value at the smallest scale that met a required minimum (more justification on this minimum below). For parameters where the number of cases was not high enough to estimate by study plot in all years, we used either the U.S. state (i.e., ME, NH, MA, RI, CT, NY, NJ) or subregional mean trait value (i.e., Gulf of Maine, Long Island Sound, New York Harbor, or New Jersey Coast). We did not perform MCnest projections for study plots that failed to meet the minimum number of observations for all parameters, though nests at excluded study plots are included in the subregional and global mean trait value estimates.

For Saltmarsh Sparrows, where individual study plot projections were run, we set a minimum sample size necessary to estimate traits at that small of a scale. We set this minimum by determining the smallest sample size of random draws where the mean of no more than one draw out of twenty was significantly different than the true mean of the measured population. Twenty observations within each draw were sufficient to estimate plot-level means for our most variable life history parameter. Conservatively, we used this minimum sample size for all our parameters that were approximately normally distributed. For three of our parameters with different distributions (renewing probability and the beginning and end dates of the breeding season) we doubled our minimum number of observations. As the start and end of the breeding season varies widely from year to year, we treated years separately when calculating the observed sample size for these parameters.

Default state lengths – For all three species we assumed that the period of rapid follicle growth lasted for four days, that eggs were laid one per day until clutch completion, and that the nestling period lasted for ten days based on values from the literature (Greenlaw et al. 1994; Shriver et al. 2011; Post and Greenlaw 2009). Because the Markov-Chain structure of MCnest requires that stages are discrete, clutch size must be modeled as an integer (to allow for one egg to be laid each day). Although clutch size does vary across latitude (see below), it does so by less than a complete egg across the range of our study plots. We thus modeled the egg-laying period as the modal clutch size for each species across all plots (four for all species). We also assumed that incubation began with the laying of either the penultimate (Nelson's sparrow: Shriver et al. 2011) or the ultimate egg (Seaside and Saltmarsh sparrows: Post and Greenlaw 2009; Greenlaw et al. 1994) and continued for the mean incubation period observed across all of our sites (after confirming that it did not vary systematically with latitude). This resulted in incubation periods of twelve (Seaside and Saltmarsh sparrows) and thirteen (Nelson's sparrows).

We set the start of the season for each year using observed values from the field. Each female for a given region was assigned a start date based on the date of the earliest field-observed nesting attempt for that year and region. We calculated the first and last nesting attempt dates for Seaside Sparrows for each year and U.S. state within the species range (i.e., CT, NY, NJ); dates for Saltmarsh Sparrow were assigned by subregion (i.e., Gulf of Maine, Long Island Sound, New York Harbor, and New Jersey Coast); and first and last breeding dates for Nelson's sparrow were calculated for each year across all U.S. states where we modeled fecundity (i.e., ME and NH). We calculated first-laid egg dates from our field observations in three ways: 1) for nests that were observed in the midst of egg-laying, we back-counted to the date the first egg was laid (assuming 1 egg laid per day); 2) for nests that hatched, we back-counted based on the estimated age of chicks at the first visit post-hatch, combined with the expected incubation and laying

interval; 3) for nests that were neither observed during egg-laying nor hatched, we used all the nests that were found during egg-laying or hatched from that year and study plot to estimate the average number of days between first egg date and nests discovery. We then subtracted this average from the discovery date for all nests without calculatable first-laid egg dates, assuming that the local habitat (e.g. height of the vegetation, accessibility of the marsh) and observers (crews included different technicians in each year) were most likely to influence discovery probability of nests. We used the date of the last field-observed nest initiation year, region, and species as the end of nest initiation (see transition probability to non-breeding discussion below).

For all three species, we set the length of the two waiting states (following either failure or fledging) in the same way for each site, because the average length of this state did not vary by plot. Upon completion of each nesting attempt, females either transitioned into renesting or post-breeding. Females that transitioned to renesting were assigned a waiting period length as a randomly selected value among the appropriate set of field-observed waiting period lengths for their species across all sites and years. Renesting females then waited their assigned interval before initiating egg-laying for a subsequent nesting attempt.

Transition probabilities among states – Once each female was assigned a season start date for the region and year, we modeled the transition probability from pre-breeding to rapid follicle growth (i.e., the first breeding stage) for Seaside and Nelson’s sparrows using the default value from MCnest (0.25 per day), which was originally calculated for white-crowned sparrows. For Saltmarsh Sparrows, however, we first calculated the mean number of days between a female’s first observed nest of the season and the first observed nest of the season in each subregion (i.e., Gulf of Maine, Long Island Sound, New York Harbor, and New Jersey Coast) and year. The inverse of this average is an estimate of the mean daily probability of breeding initiation, assuming that the probability of a female entering into breeding from pre-breeding is uniform across that period. This resulted in a daily transition probability of 0.04 for all subregions and years for Saltmarsh Sparrows.

For Seaside and Nelson’s sparrows we modeled the transition probability from those states with an active nest (laying, incubating, or brooding) to those without (waiting following a successful or waiting following a failed nesting attempt) using the daily probabilities of failure due to either flooding or predation estimated independently for each U.S. state. For Saltmarsh Sparrows, where we had a higher sample size for nests, we used the failure probabilities estimated for each study plot.

Further, because of the higher sample size for Saltmarsh Sparrow nests, we were able to allow flooding probability to covary with the local tidal height. Nest flooding probability is not a linear function of observed water depth due to the relatively homogeneous elevation profile of tidal marshes. Flooding risk is low until water spills over the stream channels of the lower marsh and into the high marsh plain. Further, the steepness of the non-linear relationship between water depth and high marsh flooding probability varies by marsh according to local microtopography. Thus, we tested a variety of transformations (Table 23) to model the threshold function of flooding probability for Saltmarsh Sparrows in the high marsh zone by study plot. We modeled nest flooding probability for each study plot as a function of the observed daily maximum observed water level at the nearest NOAA station to incorporate flooding from both astronomical tides and storm surges. We used second order Akaike’s Information Criterion (AIC_c) to compare candidate model transformations while accounting for small sample size, using the criteria that models with $\Delta AIC_c < 2.0$ were equivalent (Akaike 1974; Burnham and Anderson 2002).

We used the top model for each study plot as the transformation of water-level data for all subsequent steps. At two study plots (Hammonasset and Lubberland Creek), we observed no depredated nests. For those study plots, we modeled overall daily nest failure probability, rather than just the component nest flooding probability, as functions of the daily observed water level data. Daily nest predation probability for Saltmarsh Sparrows at each site was modeled as a constant transition probability throughout the breeding season and among years.

Table 23. Sample sizes and transformations for modeling tide-level-dependent failure probabilities for Saltmarsh Sparrows by study plot, 2011-2013.

Study Plot	State	Nests Observed	Observations (visits)	Exposure Days	Nests with Identified Females	Nest failure probability transformation
Oyster Creek	NJ	30	80	244	10	(daily water level) ⁴
Mullica Wilderness	NJ	70	178	588	40	(daily water level) ⁴
AT&T	NJ	68	205	659	36	(daily water level) ⁴
Parker River	MA	26	106	339	26	(daily water level) ⁴
Jones Creek	ME	78	337	886	78	10 [^] (-daily water level)
Nonesuch River	ME	28	124	308	28	(daily water level) ⁴
Libby River ¹	ME	4	NA	NA	4	N/A
Scarborough Marsh	ME	58	235	593	58	(daily water level) ⁴
East River	CT	60	145	511	24	10 [^] (-daily water level)
Hammonasset	CT	50	140	486	33	2 [^] (-daily water level)
Pattaganset ¹	CT	5	NA	NA	2	N/A
Waterford ¹	CT	1	NA	NA	0	N/A
Barn Island	CT	33	62	238	8	1.5 [^] (-daily water level)
Eldridge Road	ME	60	228	576	60	2 [^] (-daily water level)
Lubberland Creek	NH	25	119	327	25	10 [^] (-daily water level)
Little River ¹	ME	4	NA	NA	2	N/A
Chapman's Landing	NH	129	700	1648	129	(daily water level) ²
John H. Chaffee	RI	28	74	263	4	(daily water level) ⁴
Sachuest Point	RI	20	33	126	0	(daily water level) ⁴
Idlewild ²	NY	6	86	326	5	(daily water level) ⁴
Four Sparrow Marsh ²	NY	15	86	326	12	(daily water level) ⁴
Sawmill Creek	NY	26	60	227	21	10 [^] (-daily water level)
Marine Nature Park ²	NY	10	86	326	7	(daily water level) ⁴

¹ Fecundity nest success was not modeled for plots with fewer than 20 observed nests across all years.

² Three plots were combined into a single "Jamaica Bay" plot due to sample size.

On the first day following the completion of a nesting attempt (due to either success or failure), females had a given probability of transitioning to the post-breeding state. Thus females could quit the breeding pool after any breeding attempt. We estimated daily quitting probabilities via logistic regressions, modeling whether or not a female was observed to renest in the field as a function of the calendar day of the completion of the previous nesting attempt. We modeled quitting probabilities for Saltmarsh Sparrows at either the study plot level or the subregion, depending on sample size. For Nelson's and Saltmarsh sparrows we used a single quitting probability for all study plots. If a nesting attempt ended, however, (by either success or failure) after the latest field-observed nest initiation date for that species, region, and year, the transition probability to post-breeding was set as 1.0. In this way we did not model any nesting attempts that began later than our field observations. If the modeled female did not quit on the first day after the completion of an attempt, it transitioned to the appropriate waiting period, as described above.

Spatial Patterns

In addition to plot by plot descriptions of nest success for all of the nesting species and estimates of seasonal fecundity for the three individually marked species, we also explored spatial correlates of nest success and fecundity for the species for which we had the most information, Saltmarsh Sparrow. Specifically, we 1) tested for differences in overall nest success and in the causes of nest failure (flooding versus predation) across the Saltmarsh Sparrow range and 2) tested whether there was a "range center" for peak seasonal fecundity.

Tradeoffs between flooding and predation in Saltmarsh Sparrows – Organismal distributions are often hypothesized to be limited by abiotic stressors at high latitudes and biotic stressors at low latitudes (Dobzhansky, 1950; MacArthur, 1984; Brown, 1995; Brown et al., 1996). Normand et al. (2009) called this the Asymmetric Abiotic Stress Limitation (AASL) hypothesis. Broadly, it postulates that a tradeoff exists between physiological hardiness, which increases fitness in stressful abiotic conditions, and competitive ability, which increases fitness in areas of low abiotic stress. The AASL hypothesis has been supported by a wide range of tests in a diverse array of species (see Parmesan et al., 2005 for a review). Absolute empirical support for this hypothesis requires quantifying demographic rates as functions of biotic and abiotic stressors across the range of a species, but the AASL hypothesis has almost never been tested with demographic data.

We directly tested the AASL hypothesis by investigating patterns of reproduction at our sites across the majority of the Saltmarsh Sparrow range. We quantified nest survival probabilities using MCEstimate (as described above), separately estimating the probability of nest loss due to biotic (predation) and abiotic (flooding) stressors. Finally, we explored how the different failure probabilities vary across the landscape, to test whether biotic stressors become increasingly important moving toward low latitudes and abiotic stressors are more important toward high latitudes, in accordance with the AASL hypothesis.

Within the Saltmarsh Sparrow breeding range, abiotic stressors follow a roughly north-south gradient. Abiotic stressors include climate, the stressor that formed the basis of the AASL hypothesis, and the magnitude of tidal flooding, which has been identified as the leading cause of Saltmarsh Sparrow nest failure across a wide geographic range (Greenlaw & Rising, 1994; Gjerdrum et al., 2005, 2008; Shriver et al., 2007). Marshes at the high-latitude edge of the Saltmarsh Sparrow range experience astronomical high tides that are almost two times greater than those experienced in more southerly marshes (Fig. 12). Conversely, in tidal marshes across the range of the Saltmarsh Sparrow, lower latitude wetlands host nest

predators that have no high-latitude analog (e.g., rice rats, *Oryzomys palustris*; Post, 1981)). Further, in a meta-analysis of all the avian taxa endemic to tidal marshes in North America, nest predation rates decreased with latitude (Greenberg et al., 2006a).

We included two covariates as potential predictors of nest depredation probabilities: latitude and serial date. We recorded the latitude and longitude of each study plot (Table 22) at its approximate center using ArcGIS version 10.1 (Environmental Systems Research Institute, Redlands, USA). We included serial date as a covariate to control for potential increases in predation throughout the breeding season as has been reported in a variety of avian taxa (see Verhulst & Nilsson, 2008 for a review).

To describe nest flooding, we used latitude, serial date, and three additional potential predictors to reflect distinct inputs to tidal marsh hydrology: maximum high tide, extremity of rare flooding events, and relative sea-level rise (Table 22). Tidal marshes are shaped by both regular flooding caused by astronomical tides and irregular flooding caused by weather. Both types of flooding contribute to marsh development and maintenance (Teal, 1986). In addition, recent anthropogenic sea-level rise has contributed to higher water levels and increased flooding of tidal marshes (Wong et al., 2014). We used latitude as a proxy for maximum high tide based on the observed relationship between the two variables

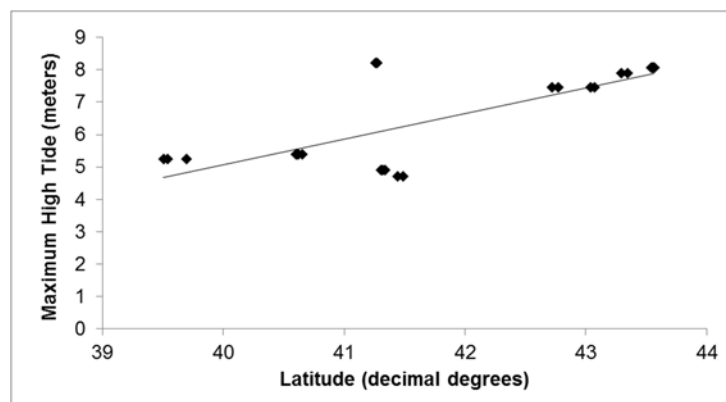


Figure 13. Maximum high tide height by study plot, as measured by maximum observed water level, May-August in 2011-2013. Maximum high tide height generally increases with latitude in the northeastern coast of the USA.

in our study region (Fig. 13) to test the AASL Hypothesis. We also included maximum observed high tide within the study period as a more direct measure of tidal height. We obtained water-level data from the National Oceanic and Atmospheric Administration (NOAA) using the observation station with available data that was closest to each demographic study plot (approximately 15-50 km by water). We used NOAA's recorded water levels above the mean daily high tide (mean higher high water datum, hereafter MHHW) for 1% annual exceedance probabilities to reflect the extremity of rare flooding events at a study plot.

Exceedance probabilities describe the likelihood that water level will surpass a given level; for example, a 1% annual exceedance probability level of 1.23 m above MHHW means that only once in 100 years will the water level likely reach 1.23 m above MHHW. This datum is corrected for local relative sea level rise. Finally, we collected linear sea-level rise estimates based on 1969-2011 water levels from Boon et al. (2012), using the location nearest to each demographic study plot (approximately 15-55 km by water). Finally, we included serial date as a covariate because monthly high tides decrease in height throughout the breeding season.

We used MCEstimate to generate daily nest survival and failure probabilities as functions of nest- and study plot-level covariates from nest monitoring data (Shaffer, 2004; Etterson & Stanley, 2008). We adopted a two-stage approach for model selection (Table 24). First, we separately compared candidate models for biotic and abiotic nest failure probabilities. We compared models containing all additive combinations of potential covariates of nest depredation probability (latitude and serial date) while

modeling nest flooding probability as constant, plus an intercept-only null model (4 candidate models total: Table 24 A). Similarly, we modeled nest depredation probability as constant while we compared all additive combinations of the potential covariates of nest flooding probability (latitude, maximum high tide, 1% exceedance value, linear sea-level rise rate, and serial date) and an intercept-only null model (32 candidate models total: Table 24 B). We used second order Akaike's Information Criteria (AIC_c) to compare candidate models in each set while accounting for sample size. Models with $AIC_c \leq 2.0$ were considered equivalent (Akaike, 1974; Burnham & Anderson, 2002). For the second stage of model selection, we built a combined model based on the best models for nest depredation and flooding probabilities, and compared the combined model to an intercept-only null model and the best models from the previous stage (Table 24 C).

Testing for a range-wide center of fecundity in Saltmarsh Sparrows – We explored the relationship between seasonal fecundity and latitude across the Saltmarsh Sparrow range. We used a linear regression in R (R Core Team 2014) to test whether latitude predicted seasonal fecundity as estimated by MCnest population projections by study plot (as described above). Specifically, we modeled a quadratic relationship between latitude and seasonal fecundity, because we predicted that seasonal fecundity would be highest at the geographic center of the Saltmarsh Sparrow range and decline linearly toward the range margins. We then tested for spatial correlation in fecundity by comparing variance within study plots to variance among study plots and by regressing all pairwise differences in fecundity by study plot to all pairwise differences in latitude. Because there were many more pairwise comparisons that were geographically close than distant, we controlled for sampling effort through subsampling. We binned pairwise differences by single degrees of latitudinal distance, and for each bin we randomly subsampled the number of comparisons in the bin with the fewest comparisons. We randomly subsampled the dataset 10 times and ran a simple linear regression between latitudinal difference and difference in seasonal fecundity for each subset of data.

Historical Changes

We estimated trends in nest density using data collected at 121 one-hectare plots that were surveyed across Connecticut from 2002-2009 (for Methods see **Nest Monitoring**, above). These plots have a standardized area, were all surveyed using the same methods, and were small enough to be thoroughly searched, making them well-suited for looking at long-term trends in the number of unique nests. For each plot, we calculated the number of unique nests found over the breeding season for Saltmarsh Sparrow, Seaside Sparrow, and Clapper Rail. Nest density over time was analyzed using Bayesian hierarchical models that account for marsh size (because larger marshes tended to be surveyed during the first years of the survey). Most plots were surveyed in only one year, but some plots were repeated, and some plots were added to marshes sampled in previous years. Consequently, we also ran a model using data just from marshes that were surveyed in multiple years, to provide a more conservative analysis that eliminates any concern about marsh size, or other marsh-specific factors, being confounded with time. We did not have enough data to conduct an analysis using this more conservative approach for Clapper Rail.

Table 24. Model comparisons for explaining the daily probability of A) nest predation, B) nest flooding, and C) nest success including failure from both sources for Saltmarsh Sparrows from Maine to New Jersey, 2011-2013.

Predictors of nest predation	Predictors of nest flooding	AIC _c	ΔAIC _c	Weight
<i>A) Model selection for predicting daily nest predation risk</i>				
latitude	intercept-only	2996.59	0	0.57
latitude + serial date	intercept-only	2997.18	0.59	0.43
intercept-only	intercept-only	3017.74	21.15	<0.01
serial date	intercept-only	3019.74	23.15	<0.01
<i>B) Model selection for predicting daily nest flooding risk</i>				
intercept-only	maximum high tide + 1% exceedance value + serial date	2988.25	0	0.35
intercept-only	latitude + maximum high tide + 1% exceedance value + serial date	2989.20	0.95	0.22
intercept-only	maximum high tide + sea level rise rate + 1% exceedance value + serial date	2989.53	1.29	0.18
intercept-only	latitude + 1% exceedance value + serial date	2991.09	2.84	0.08
intercept-only	latitude + maximum high tide + sea level rise rate + serial date+ 1% exceedance value	2991.19	2.94	0.08
intercept-only	sea level rise rate + 1% exceedance value + serial date	2992.64	4.39	0.04
intercept-only	latitude + sea level rise rate + 1% exceedance value + serial date	2993.03	4.79	0.03
intercept-only	1% exceedance value + serial date	2996.30	8.05	0.01
intercept-only	maximum high tide + 1% exceedance value	3002.21	13.97	<0.01
intercept-only	maximum high tide + sea level rise rate + serial date	3002.40	14.15	<0.01
intercept-only	latitude + maximum high tide + sea level rise rate + serial date	3003.43	15.18	<0.01
intercept-only	latitude + maximum high tide + 1% exceedance value	3004.14	15.89	<0.01
intercept-only	maximum high tide + sea level rise rate + 1% exceedance value	3004.21	15.97	<0.01
intercept-only	latitude + maximum high tide + serial date	3005.09	16.84	<0.01
intercept-only	latitude + 1% exceedance value	3005.15	16.91	<0.01
intercept-only	latitude + sea level rise rate + serial date	3005.35	17.10	<0.01

Table 24. Continued

Predictors of nest predation	Predictors of nest flooding	AIC _c	ΔAIC _c	Weight
<i>B) Model selection for predicting daily nest flooding risk (continued)</i>				
intercept-only	serial date	3005.86	17.61	<0.01
intercept-only	1% exceedance value	3005.90	17.66	<0.01
intercept-only	latitude + maximum high tide + sea level rise rate + 1% exceedance value	3005.91	17.66	<0.01
intercept-only	maximum high tide + serial date	3006.17	17.93	<0.01
intercept-only	sea level rise rate + 1% exceedance value	3006.20	17.95	<0.01
intercept-only	latitude + sea level rise rate + 1% exceedance value	3006.81	18.56	<0.01
intercept-only	sea level rise rate + serial date	3007.15	18.90	<0.01
intercept-only	latitude + serial date	3007.83	19.58	<0.01
intercept-only	maximum high tide + sea level rise rate	3013.02	24.77	<0.01
intercept-only	latitude + maximum high tide + sea level rise rate	3014.20	25.95	<0.01
intercept-only	maximum high tide + 1% exceedance value + serial date	2988.25	0	0.35
intercept-only	latitude + maximum high tide + 1% exceedance value + serial date	2989.20	0.95	0.22
intercept-only	maximum high tide + sea level rise rate + 1% exceedance value + serial date	2989.53	1.29	0.18
intercept-only	latitude + 1% exceedance value + serial date	2991.09	2.84	0.08
intercept-only	latitude + maximum high tide + sea level rise rate + serial date + 1% exceedance value	2991.19	2.94	0.08
intercept-only	sea level rise rate + 1% exceedance value + serial date	2992.64	4.39	0.04
intercept-only	latitude + sea level rise rate + 1% exceedance value + serial date	2993.03	4.79	0.03
intercept-only	1% exceedance value + serial date	2996.30	8.05	0.01
intercept-only	maximum high tide + 1% exceedance value	3002.21	13.97	<0.01
intercept-only	maximum high tide + sea level rise rate + serial date	3002.40	14.15	<0.01
intercept-only	latitude + maximum high tide + sea level rise rate + serial date	3003.43	15.18	<0.01

Table 24. Continued

Predictors of nest predation	Predictors of nest flooding	AIC _c	ΔAIC _c	Weight
<i>B) Model selection for predicting daily nest flooding risk (continued)</i>				
intercept-only	latitude + maximum high tide + 1% exceedance value	3004.14	15.89	<0.01
intercept-only	maximum high tide + sea level rise rate + 1% exceedance value	3004.21	15.97	<0.01
intercept-only	latitude + maximum high tide + serial date	3005.09	16.84	<0.01
intercept-only	latitude + 1% exceedance value	3005.15	16.91	<0.01
intercept-only	latitude + sea level rise rate + serial date	3005.35	17.10	<0.01
intercept-only	serial date	3005.86	17.61	<0.01
intercept-only	1% exceedance value	3005.90	17.66	<0.01
intercept-only	latitude + maximum high tide + sea level rise rate + 1% exceedance value	3005.91	17.66	<0.01
intercept-only	maximum high tide + serial date	3006.17	17.93	<0.01
intercept-only	sea level rise rate + 1% exceedance value	3006.20	17.95	<0.01
intercept-only	latitude + sea level rise rate + 1% exceedance value	3006.81	18.56	<0.01
intercept-only	sea level rise rate + serial date	3007.15	18.90	<0.01
intercept-only	latitude + serial date	3007.83	19.58	<0.01
intercept-only	maximum high tide + sea level rise rate	3013.02	24.77	<0.01
intercept-only	latitude + maximum high tide + sea level rise rate	3014.20	25.95	<0.01
intercept-only	latitude + sea level rise rate	3015.25	27.01	<0.01
intercept-only	sea level rise rate	3016.36	28.12	<0.01
intercept-only	latitude + maximum high tide	3016.38	28.13	<0.01
intercept-only	intercept-only	3017.74	29.50	<0.01
intercept-only	latitude	3018.26	30.01	<0.01
intercept-only	maximum high tide	3019.63	31.39	<0.01

Table 24. Continued

Predictors of nest predation	Predictors of nest flooding	AIC _c	ΔAIC _c	Weight
<i>C) Model selection for predicting daily nest success with combined daily predation and flooding risk</i>				
latitude	maximum high tide + 1% exceedance value + serial date	2967.73	0	>0.99
intercept-only	maximum high tide + 1% exceedance value + serial date	2988.25	20.52	<0.01
latitude	intercept-only	2996.59	28.86	<0.01
intercept-only	intercept-only	3017.74	50.02	<0.01

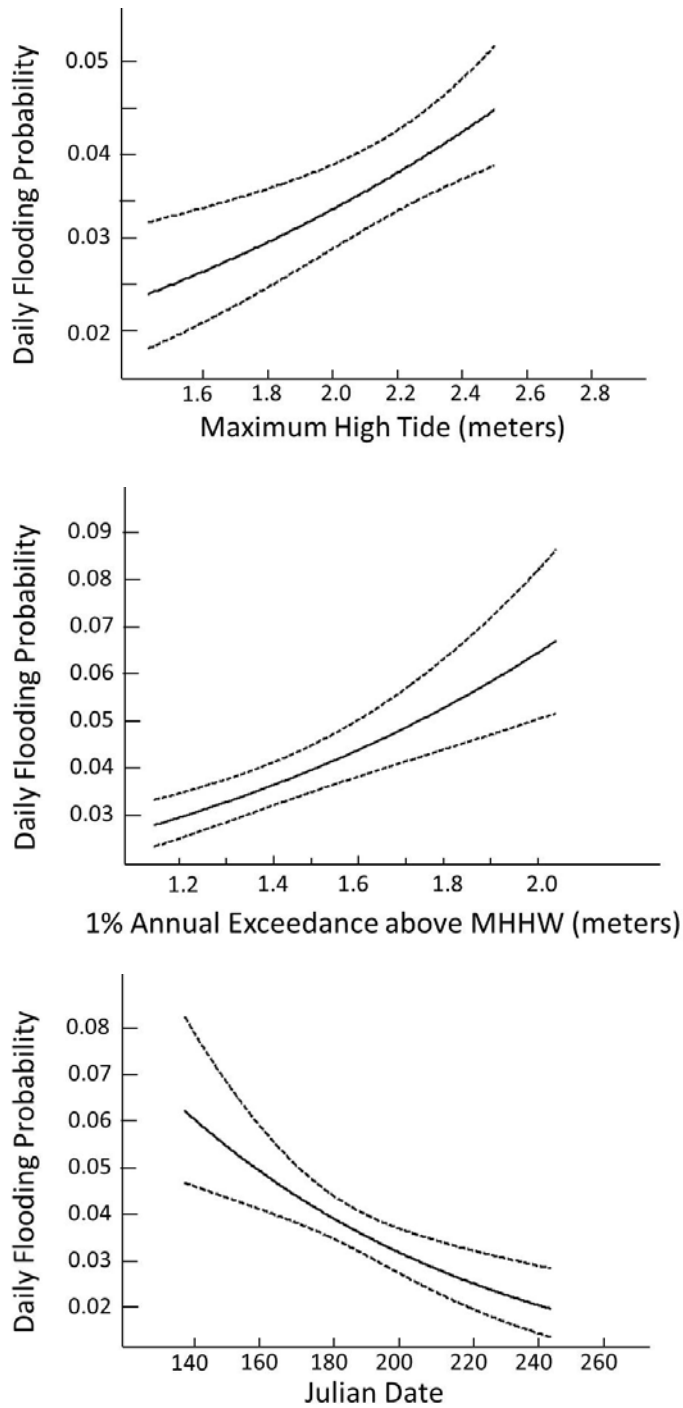


Figure 14. Daily nest flooding probability of Saltmarsh Sparrows was best predicted by maximum observed high tide during the study period (May-August, 2011-2013); meters above mean higher high water (MHHW, the monthly high tide) for the 1% annual exceedance probability; and serial date.

Results

Nest success & seasonal fecundity

From 2011-2013 we found a total of 45 Clapper Rail nests (Table 25), 142 Willet nests (Table 26), 80 Nelson's sparrow nests (Table 27), 349 Seaside Sparrow nests (Table 28), 1,022 Saltmarsh Sparrow nests (Table 29), and 6 American black duck nests. Among study plots with Clapper Rails, nest density ranged from 0.05 (Oyster Creek, Edwin B. Forsythe NWR, NJ) to 0.97 (Idlewild, NY) nests per hectare per year with a mean ($\pm$ SD) of 0.36 ± 0.32 nests per hectare per year. Among plots with nesting Willets, nest density ranged from 0.08 (John H. Chaffee NWR, RI) to 1.62 (Four Sparrow Marsh, NY) nests per hectare per year with a mean of 0.39 ± 0.35 nests per hectare per year. Among plots with nesting Nelson's sparrows, nest density ranged from 0.04 (Parker River NWR, MA) to 1.42 (Scarborough Marsh, ME) nests per hectare per year with a mean of 0.42 ± 0.40 nests per hectare per year. Seaside sparrow nesting density was much higher and ranged from 0.17 (Barn Island, CT) to 22.67 (Idlewild, NY) nests per hectare per year with a mean of 1.83 ± 4.70 nests per hectare per year. Saltmarsh sparrow nesting density was the highest on average, ranging from 0.04 (Parker River NWR, MA) to 23.52 (Four Sparrow Marsh, NY) nests per hectare per year with a mean of 2.35 ± 3.47 nests per hectare per year. We found one American black duck nest along the East River in Connecticut, two nests in the Barn Island Wildlife Management Area in Connecticut, and three nests in Edwin B. Forsythe NWR in New Jersey.

Daily nest success probability ($\pm$ SE) for Clapper Rails ranged from 0.97 ± 0.02 (Oyster Creek, NJ) to 1.0 ± 0.0 (Hammonasset, CT, where all eight nests successfully hatched) with a mean ($\pm$ SE) of 0.99 ± 0.01 (Table 25). Willet nest success ranged from 0.88 ± 0.05 (Scarborough Marsh, ME) to 0.97 ± 0.02 (Mullica Wilderness, NJ) with a mean of 0.94 ± 0.01 (Table 26). Nest success rates for Nelson's sparrows ranged from 0.89 (Eldridge Road, Rachel Carson NWR, ME) to 0.98 (Chapman's Landing, NH) with a mean of 0.93 ± 0.01 (Table 27). Seaside sparrow daily success probability ranged from 0.88 (Hammonasset State Park, CT) to 0.96 (Oyster Creek, NJ) with a mean of 0.93 ± 0.01 as well (Table 28). Saltmarsh sparrow nest success ranged from 0.86 (Idlewild, NY) to 0.97 (Parker River NWR, MA) with a mean, again, of 0.93 ± 0.01 (Table 29).

Given the low rate of renesting in both Clapper Rail and Willet, nest success is likely a good proxy for seasonal fecundity (although our estimates of nest success for these precocial species do not include offspring mortality post-hatching). Among the three sparrow species, however, where renesting is more common, our estimates of seasonal fecundity varied. For Nelson's sparrows, fecundity was highest at the New Hampshire sites (mean [95% CI] = 1.40 [1.32–1.47] broods per female per season; 3.93 [3.7–4.13] offspring per female per season) which are further upriver than the Maine sites (0.71 [0.59–0.84] broods per female per season; 1.99 [1.67–2.36] offspring per female per season). For Seaside Sparrows, fecundity was highest in New Jersey (0.88 [0.75–1.0] broods per female per season; 2.40 [2.04–2.73] offspring per female per season) and declined to the north (Table 28). Saltmarsh sparrow fecundity was highest in New Hampshire (0.64 [0.56–0.73] broods per female per season; 1.89 [1.63–2.14] offspring per female per season), although fecundity was highly variable across sites and years (Fig. 15).

Table 25. Nest monitoring results for Clapper Rails in Connecticut, New York, and New Jersey, 2011-2013.

Study Plot	State	Latitude (°N)	Longitude (°E)	Site Area (ha)	# Nests	Mean Yearly Nests / ha	Daily Nest Survival Probability ¹ (95% CI)
Oyster Creek	NJ	39.5056	-74.4268	18.5	9	0.162	0.972 (0.92 – 0.991)
Mullica Wilderness	NJ	39.5363	-74.4392	17.4	1	0.057	
<i>New Jersey Summary</i>					10	0.136	0.978 (0.933 – 0.993)
Four Sparrow							
Marsh	NY	40.6001	-73.9054	1.2	1	0.811	
Sawmill Creek	NY	40.6088	-74.1933	3.9	1	0.256	
Marine Nature Park	NY	40.6204	-73.6213	3.8	3	0.798	
Idlewild	NY	40.6530	-73.7508	3.1	3	0.972	
<i>New York Summary</i>					8	0.709	0.983 (0.935 – 0.996)
Hammonasset	CT	41.2611	-72.5491	13.2	8	0.202	1.000
East River	CT	41.2725	-72.6520	19.0	19	0.332	0.989 (0.967 – 0.996)
<i>Connecticut Summary</i>					27	0.268	0.991 (0.973 – 0.997)

¹ Nest survival probabilities were only calculated for plots or states with at least seven observed nests

Table 26. Nest monitoring results for Willets in New Jersey, New York, and New England, 2011-2013.

Site	State	Latitude (°N)	Longitude (°E)	Site Area (ha)	# Nests	Mean Yearly Nests / ha	Daily Nest Survival Probability ¹ (95% CI)
Oyster Creek	NJ	39.5056	-74.4268	18.5	34	0.180	0.964 (0.943 – 0.977)
Mullica Wilderness	NJ	39.5363	-74.4392	17.4	12	0.229	0.973 (0.92 – 0.991)
AT&T	NJ	39.6973	-74.2137	14.3	10	0.795	0.944 (0.86 – 0.979)
<i>New Jersey Summary</i>					56	0.402	0.963 (0.945 – 0.975)
Four Sparrow							
Marsh	NY	40.6001	-73.9054	1.2	2	1.622	
Sawmill Creek	NY	40.6088	-74.1933	3.9	2	0.256	
Marine Nature							
Park	NY	40.6204	-73.6213	3.8	3	0.798	
<i>New York Summary</i>					7	0.733	0.924 (0.81 – 0.972)
Hammonasset	CT	41.2611	-72.5491	13.2	16	0.404	0.956 (0.916 – 0.977)
East River	CT	41.2725	-72.6520	19.0	17	0.298	0.937 (0.883 – 0.967)
Pattaganset	CT	41.3179	-72.2129	8.4	1	0.119	
Barn Island	CT	41.3383	-71.8686	23.5	23	0.327	0.893 (0.833 – 0.933)
<i>Connecticut Summary</i>					57	0.321	0.934 (0.91 – 0.952)
John H. Chaffee	RI	41.4452	-71.4639	12.1	1	0.083	
<i>Rhode Island Summary</i>					1	0.083	
Jones Creek	ME	43.5421	-70.3509	11.5	8	0.348	0.965 (0.872 – 0.991)
Nonesuch River	ME	43.5554	-70.3257	13.9	3	0.216	
Scarborough River	ME	43.5655	-70.3596	9.8	10	0.339	0.883 (0.761 – 0.947)
<i>Maine Summary</i>					21	0.322	0.926 (0.866 – 0.96)

¹ Nest survival probabilities were only calculated for plots with at least seven observed nests.

Table 27. Nest monitoring results for Nelson's Sparrows in New England, 2011-2013¹.

Site	State	Latitude (°N)	Longitude (°E)	Site Area (ha)	# Nests	Mean Yearly Nests / ha	Daily Nest Survival Probability ² (95% CI)	Seasonal Fecundity ³ (95% CI)
Parker River	MA	42.7749	-70.8105	27.9	1	0.036		
<i>Massachusetts Summary</i>					1	0.036		
Chapman's							0.975	
Landing	NH	43.0411	-70.9239	12.0	11	0.305	(0.935 – 0.991)	
Lubberland								
Creek	NH	43.0748	-70.9119	8.1	1	0.124		
<i>New Hampshire Summary</i>					12	0.260	0.977 (0.94 – 0.991)	1.40 (1.32 – 1.47)
Eldridge Road	ME	43.2926	-70.5725	11.5	11	0.320	0.892 (0.827 – 0.934)	
Jones Creek	ME	43.5421	-70.3509	11.5	4	0.174		
Nonesuch							0.927	
River	ME	43.5554	-70.3257	13.9	17	0.552	(0.88 – 0.957)	
Libby River	ME	43.5567	-70.3128	13.0	2	0.154		
Scarborough							0.917	
Marsh	ME	43.5655	-70.3596	9.8	33	1.120	(0.883 – 0.941)	
<i>Maine Summary</i>					67	0.504	0.917 (0.893 – 0.936)	0.71 (0.59 – 0.84)

¹ Based on plumage identification of the attending female (hybrid nests are not included in either this table or that of Saltmarsh Sparrows)

² Nest survival probabilities were only calculated for plots or states with at least seven observed nests

³ Estimated number of successful broods per female per year (mean brood size of successful nests across all plots is 2.81 fledglings)

Table 28. Nest monitoring results for Seaside Sparrows in Connecticut, New York, and New Jersey, 2011-2013.

Site	State	Latitude (°N)	Longitude (°E)	Site Area (ha)	# Nests	Mean Yearly Nests / ha	Daily Nest Survival Probability ¹ (95% CI)	Seasonal Fecundity ² (95% CI)
Oyster Creek	NJ	39.5056	-74.4268	18.5	116	2.090	0.961 (0.947 – 0.972)	
Mullica Wilderness	NJ	39.5363	-74.4392	17.4	52	0.994	0.959 (0.94 – 0.972)	
AT&T	NJ	39.6973	-74.2137	14.3	49	1.146	0.924 (0.891 – 0.947)	
<i>New Jersey Summary</i>					217	1.410	0.953 (0.942 – 0.962)	0.88 (0.75 – 1.00)
Sawmill Creek	NY	40.6088	-74.1933	3.9	5	0.640		
Idlewild	NY	40.6530	-73.7508	3.1	72	11.661	0.933 (0.909 – 0.951)	
<i>New York Summary</i>					77	6.150	0.936 (0.913 – 0.953)	0.71 (0.62 – 0.81)
Hammonasset	CT	41.2611	-72.5491	13.2	15	0.379	0.877 (0.802 – 0.926)	
East River	CT	41.2725	-72.6520	19.0	22	0.386	0.889 (0.825 – 0.932)	
Barn Island	CT	41.3383	-71.8686	23.5	18	0.256	0.927 (0.881 – 0.956)	
<i>Connecticut Summary</i>					55	0.340	0.903 (0.869 – 0.929)	0.47 (0.31 – 0.62)

¹ Nest survival probabilities were only calculated for plots or states with at least seven observed nests

² Estimated number of successful broods per female per year (mean brood size of successful nests across all plots is 2.73 fledglings)

Table 29. Nest monitoring results for Saltmarsh Sparrows in New England, New York, and New Jersey, 2011-2013¹.

Site	State	Latitude (°N)	Longitude (°E)	Site Area (ha)	# Nests	Mean Yearly Nests / ha	Daily Nest Survival Probability ² (95% CI)	Seasonal Fecundity ³ (95% CI)
Oyster Creek	NJ	39.5056	-74.4268	18.5	43	0.775	0.925 (0.889 – 0.950)	0.483 (0.380 – 0.587)
Mullica Wilderness	NJ	39.5363	-74.4392	17.4	92	1.760	0.936 (0.915 – 0.952)	0.54 (0.430 – 0.653)
AT&T	NJ	39.6973	-74.2137	14.3	111	2.596	0.930 (0.904 – 0.95)	0.487 (0.387 – 0.587)
<i>New Jersey Summary</i>					246	1.710	0.932 (0.918 – 0.943)	0.503 (0.399 – 0.609)
Four Sparrow Marsh	NY	40.6001	-73.9054	1.2	40	16.218	0.962 (0.927 – 0.981)	0.585 (0.480 – 0.695)
Sawmill Creek	NY	40.6088	-74.1933	3.9	41	5.247	0.926 (0.882 – 0.955)	0.595 (0.470 – 0.72)
Marine Nature Park	NY	40.6203	-73.6212	3.8	22	5.855	0.918 (0.829 – 0.963)	0.585 (0.480 – 0.695)
Idlewild	NY	40.6530	-73.7508	3.1	11	3.563	0.856 (0.703 – 0.937)	0.585 (0.480 – 0.695)
<i>New York Summary</i>					114	8.725	0.932 (0.905 – 0.952)	0.59 (0.475 – 0.708)
Hammonasset	CT	41.2611	-72.5491	13.2	59	1.492	0.929 (0.904 – 0.948)	0.380 (0.293 – 0.47)
East River	CT	41.2725	-72.652	19.0	69	1.209	0.917 (0.888 – 0.939)	0.370 (0.277 – 0.467)
Waterford	CT	41.3052	-72.1058	3.4	1	0.296		
Pattaganset	CT	41.3179	-72.2129	8.4	5	0.298		
Barn Island	CT	41.3383	-71.8686	23.5	40	0.569	0.868 (0.813 – 0.909)	0.163 (0.117 – 0.213)
<i>Connecticut Summary</i>					174	0.892	0.915 (0.898 – 0.929)	0.304 (0.229 – 0.383)
John H. Chaffee	RI	41.4452	-71.4638	12.1	36	0.992	0.964 (0.927 – 0.982)	0.687 (0.553 – 0.817)
Sachuest Point	RI	41.4891	-71.2496	3.7	35	3.141	0.860 (0.780 – 0.914)	0.240 (0.137 – 0.337)
<i>Rhode Island Summary</i>					71	2.067	0.934 (0.908 – 0.953)	0.463 (0.345 – 0.577)
Parker River	MA	42.7749	-70.8105	27.9	26	0.311	0.970 (0.945 – 0.983)	0.373 (0.293 – 0.457)
<i>Massachusetts Summary</i>					26	0.311	0.966 (0.943 – 0.98)	0.373 (0.293 – 0.457)

Table 29. Continued.

Site	State	Latitude (°N)	Longitude (°E)	Site Area (ha)	# Nests	Nests / ha	Daily Nest Survival Probability ² (95% CI)	Seasonal Fecundity ³ (95% CI)
Chapman's Landing	NH	43.0411	-70.9239	12.0	129	3.578	0.967 (0.958 – 0.975)	0.753 (0.663 – 0.843)
Lubberland Creek	NH	43.0748	-70.9119	8.1	25	1.550	0.962 (0.939 – 0.976)	0.48 (0.395 – 0.56)
<i>New Hampshire Summary</i>					154	2.767	0.966 (0.958 – 0.973)	0.644 (0.556 – 0.73)
Eldridge Road	ME	43.2926	-70.5725	11.5	62	1.803	0.915 (0.891 – 0.934)	0.343 (0.247 – 0.437)
Little River	ME	43.3441	-70.5400	6.9	2	0.289		
Jones Creek	ME	43.5421	-70.3509	11.5	79	3.435	0.963 (0.948 – 0.973)	0.705 (0.615 – 0.795)
Nonesuch River	ME	43.5554	-70.3257	13.9	29	0.696	0.92 (0.881 – 0.947)	0.337 (0.233 – 0.437)
Libby River	ME	43.5567	-70.3128	13.0	4	0.309		
Scarborough Marsh	ME	43.5655	-70.3596	9.8	61	2.070	0.938 (0.915 – 0.955)	0.493 (0.387 – 0.6)
<i>Maine Summary</i>					237	1.629	0.939 (0.928 – 0.948)	0.448 (0.348 – 0.546)

¹ Based on plumage identification of the attending female (hybrid nests are not included in either this table or that of Nelson's Sparrows)

² Nest survival probabilities were only calculated for plots or states with at least seven observed nests.

³ Estimated number of successful broods per female per year (mean brood size of successful nests across all plots is 2.93 fledglings).

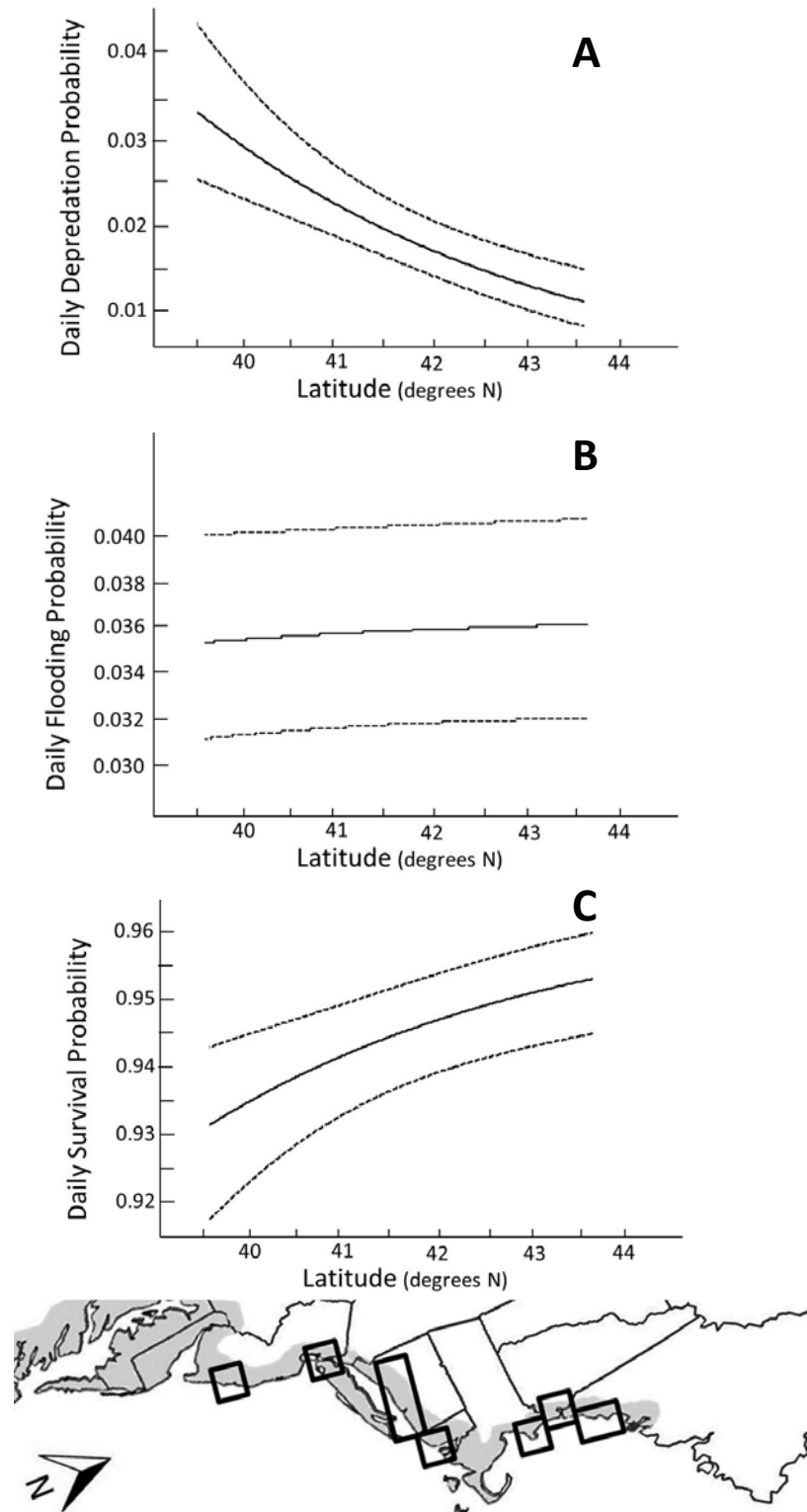


Figure 15. A) Significant decreased in daily nest predation probability for Saltmarsh Sparrows as a function of increasing latitude; B) Daily nest flooding probability is independent of latitude; C) Total daily nest survival probability increased modeled with latitude.

Spatial patterns

Tradeoffs between flooding and predation in Saltmarsh Sparrows – Despite much local heterogeneity, we observed clear large-scale patterns in nest failure probabilities of Saltmarsh Sparrows. The model containing only latitude best predicted daily nest predation probability ($w_i=0.57$) and performed much better than the null model ($\Delta AIC_c=23.15$, $w_i<0.01$). Nest predation probability increased moving toward low latitudes (Fig. 15). An additive combination of date, maximum high tide, and extremity of rare flooding events best predicted daily nest flooding probability ($w_i=0.43$) and performed much better than the null model ($\Delta AIC_c=29.5$, $w_i<0.01$). Nest flooding probability decreased throughout the breeding season, increased with increasing maximum high tide, and increased with increasing extremity of rare flooding events (Fig. 14). The nest flooding model using latitude as the sole predictive variable performed worse than the null model ($\Delta AIC_c=30.01$, $w_i<0.01$; Fig. 15). The combined model (nest depredation probability predicted by latitude, nest flooding probability predicted by serial date, maximum high tide, and exceedance value; $w_i=1.0$) predicted nest failure probabilities better than the top model for nest depredation probability ($\Delta AIC_c=28.86$, $w_i<0.01$), the top model for nest flooding probability ($\Delta AIC_c=20.52$, $w_i<0.01$), and the null model ($\Delta AIC_c=50.2$, $w_i<0.01$). Total daily nest survival probability increased toward the high-latitude edge of the Saltmarsh Sparrow breeding range (Fig. 14). Total nest survival probability decreased with increasing exceedance value and increased throughout the breeding season. There was no relationship between maximum high tide and total nest survival probability.

Our findings are consistent with the AASL hypothesis that abiotic stressors (flooding) pose greater risks to population growth at high latitudes than biotic stressors (depredation). Further, we found that nest depredation probability varied with latitude, suggesting that biotic stressors become increasingly important moving toward low latitudes. Nest flooding probability did not vary with latitude, however. Instead, nest flooding probability was best predicted by an additive combination of three variables that vary independently from latitude. Therefore, in opposition to modern formulations of the AASL hypothesis, our results suggest that in this system, there is not a direct tradeoff between physiological tolerance and competitive ability. Without experimental manipulation, we cannot be certain that nest flooding and nest predation probabilities limit Saltmarsh Sparrow populations where they are highest. We can conclude, however, that the relative importance of each competing stressor changes across the species range and through time.

Testing for a range-wide center of fecundity in Saltmarsh Sparrows – Saltmarsh sparrow clutch size varied by study plot ($P < 0.01$ compared to the intercept-only null model) and there was a trend of increasing clutch size with latitude, but it was only marginally significant ($F_{1,815} = 3.5$, $P = 0.06$ $R^2 < 0.01$). The difference in mean clutch size between the study plots at the lowest and highest latitudes, however, was less than one egg, so we used the global modal clutch size of four eggs in MCnest projections at all study plots. The global mean clutch size $\pm$ SD was 3.66 ± 0.70 eggs. Brood size did not vary by study plot ($P = 0.13$ compared to the intercept-only model), and thus the global mean brood size of 2.73 ± 1.05 was used in all MCnest projections for all study plots. Incubation interval did not vary by study plot ($P = 0.27$ compared to the intercept-only model), and the global mean incubation interval was 12.09 ± 0.98 days (inclusive of the final egg-laying day and the day of the first hatch) and the mode across all study plots was 12 days. Thus, we used 12 days as the incubation interval in MCnest projections for all study plots. Number of nesting attempts varied by study plot ($P < 0.01$ compared to the intercept-only model) and increased with latitude ($F_{1,494} = 12.2$, $P < 0.01$, $R^2 = 0.02$; Fig. 16). Only four study plots had enough observations to characterize number of nesting attempts at the study-plot level by our conservative

minimum. Pooled subregional means $\pm$ SD were as follows: Gulf of Maine = 1.29 ± 0.51 nesting attempts per female; Long Island Sound = 1.10 ± 0.29 ; NY Harbor = 1.36 ± 0.60 ; NJ Coast = 1.06 ± 0.24 . Earliest first egg date varied by study plot ($F=2.0_{22,30}$, $p=0.04$) and increased with latitude ($F_{1,51} = 11.2$, $P < 0.01$, $R^2 = 0.16$; Fig. 16).

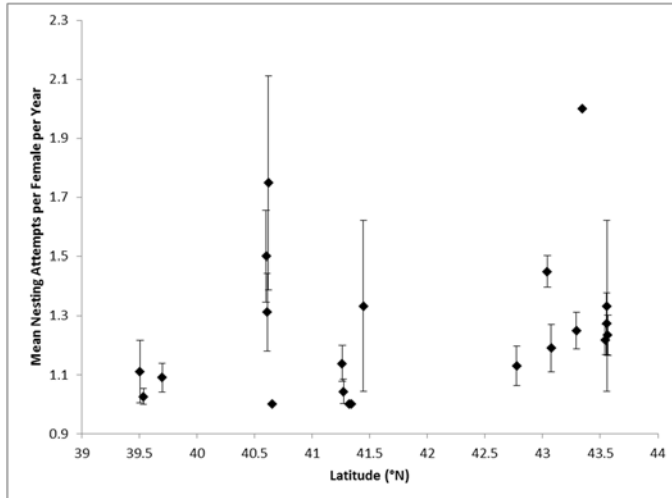


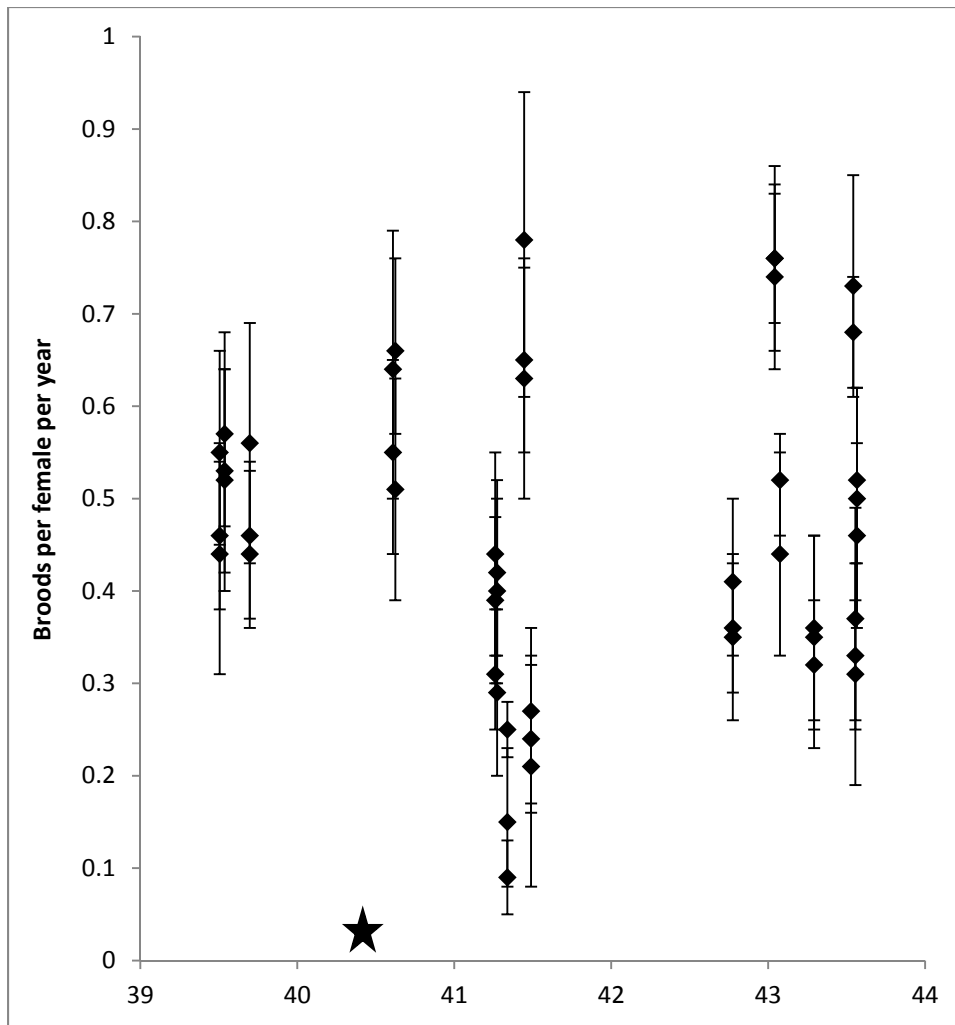
Figure 16. Mean ($\pm$ SE) of the number of nesting attempts observed by marked female Saltmarsh Sparrows each year across our study plots.

Seasonal fecundity did not vary with latitude across the Saltmarsh Sparrow range ($F_{2,44}=1.5$, $p=0.23$ $R^2=0.02$; Fig. 17). We observed significantly more variance in seasonal fecundity estimates among than within study plots ($F_{1,1079}=40.8$, $p<0.01$, $R^2=0.04$). At the scale of U.S. states, however, the variance in seasonal fecundity was similar among and within states ($F_{1,1036}=0.2$, $p=0.66$). Together this suggests that fecundity within plots is consistent (at the time scales we observed), but spatial heterogeneity in fecundity is high both within and among subregions. Oddly, similarity in seasonal fecundity estimates increased with latitudinal distance between projections ($F_{1,1079}=5.3$, $p=0.03$, $R^2=0.003$). This pattern was consistent in 9 of the 10 subsamples used

to control for sampling effort across the latitudinal range. This result is likely due to the higher heterogeneity of fecundity estimates in sites along the Long Island Sound than elsewhere (Fig. 17). Once we removed these study plots, there was no relationship between geographic distance and similarity in seasonal fecundity ($F_{1,494}=0.2$, $P = 0.63$). This pattern was consistent in 10 of 10 subsamples.

Historical Changes

The nest density of specialist saltmarsh nesting birds is declining in Connecticut for Saltmarsh Sparrow, Seaside Sparrow, and Clapper Rail, with Saltmarsh Sparrows showing the strongest decline (Fig. 18A). Estimates from the complete dataset show declines over time with credible intervals that do not overlap zero for all three species (Figure 18A). Estimates from just marshes that were surveyed in multiple years show the same pattern for Saltmarsh Sparrow, but with slightly larger credible intervals, while the trend for Seaside Sparrow was centered on zero. Marsh size was not a strong predictor of nest density for any species.



Latitude (degrees N)

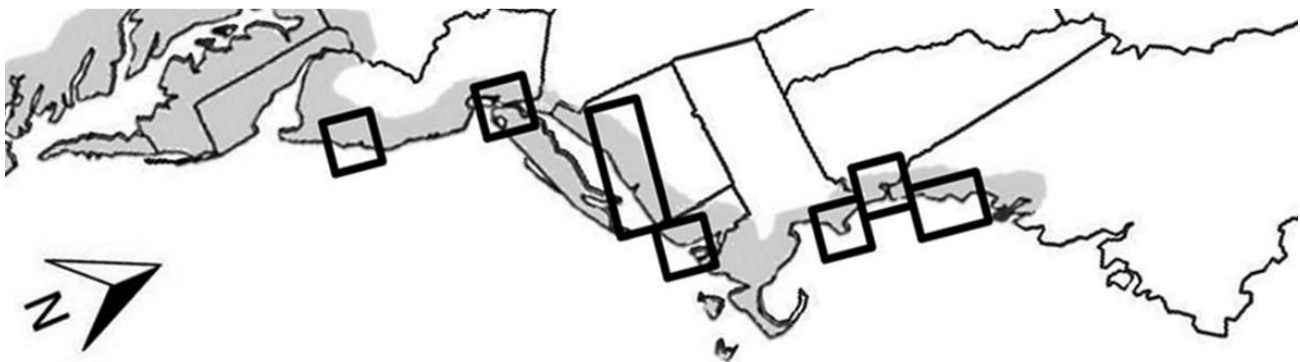


Figure 17. Annual seasonal fecundity for Saltmarsh Sparrows by study plot ($\pm$ 95% CI). Star denotes the geographic center of the Saltmarsh Sparrow's latitudinal breeding range. The map of the northeast US coastline beneath the figure is aligned to indicate the region for each of the estimated fecundity values above.

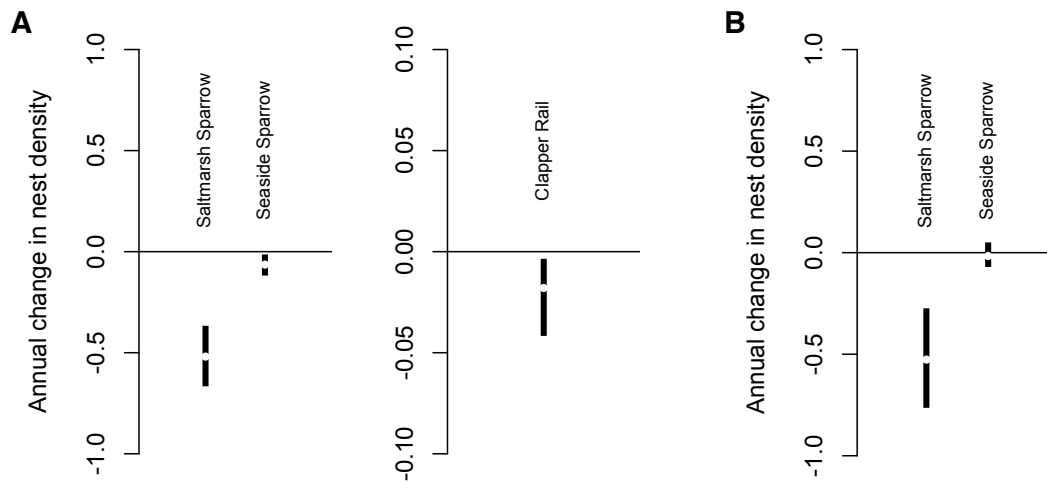


Figure 18. Change in the number of nests per hectare for Saltmarsh Sparrow, Seaside Sparrow, and Clapper Rail in Connecticut. Panel A shows estimates using data from all plots ($n = 121$ plots). Panel B shows estimates using only data from marshes that were surveyed in multiple years: Hammonasset State Park (Madison), East River marsh (Madison/Guilford), Connecticut River complex (Old Lyme), and Barn Island Wildlife Management Area (Stonington). White dots are mean estimates and black bars are 95% credible intervals.

Conclusions

We report nest densities and daily failure probabilities for our five focal species across 23 study plots and three years of study. Further, we estimated seasonal fecundity (successful broods per female annually) for the three sparrow species. Nelson's Sparrow reproductive success exhibited no large-scale patterns across the survey area but was considerably higher at the single well-sampled upriver marsh compared to multiple coastal sites. Seaside Sparrow fecundity was greatest in our most southern plots (toward the center of their range) and generally declined to the north. The study plot with the highest Saltmarsh sparrow fecundity was in New Hampshire, but fecundity was highly variable across the range (the nearest plot to the maximum fecundity exhibited a fecundity value in the 48th percentile of those measured). Flooding risk is the highest cause of nest loss across the Saltmarsh Sparrow range, but varied locally, while nest predation increases on average from north to south. Female reproductive behavior varied with plot as well, with more northern females exhibiting a higher probability of renesting following nest loss and a longer breeding season in general. The high spatial heterogeneity in both flooding risk and fecundity suggests that Saltmarsh Sparrow reproductive success is driven more by local than regional processes and may respond to local management actions. Clapper Rail and Seaside and Saltmarsh sparrows all showed significant declines in nest densities over the last decade in Connecticut (the only area with data available), mirroring the trends reported in singing males across USFWS Region 5 (**V. Population Trends**).

VII. Sparrow Survival Methods

Methods

Field methods

We conducted standardized mist-netting at 21 plots in major marsh complexes from New Jersey to Maine, USA (Table 30). We surveyed most plots in 2011, 2012, 2013, and 2014 (see Table 30 for specific years each plot was surveyed). Plots were 1-28 ha and divided into 1-5 subplots that could be surveyed using two or three arrays of six, 12-m mist-nets in a continuous string. Each subplot was surveyed on three days each year, distributed across the summer, cycling through the subplots such that each was visited once before the next round of visits. The survey period at each site began between mid-May and early June, with lower latitude sites starting earlier, and corresponded with the period at which most individuals at a plot could reasonably be assumed to be resident. Standardized mist-netting ended once three visits were made to each subplot, and ran no later than mid-August. Each visit consisted of three hours of mist-netting that was completed by approximately 11:00. Mist-netting was not conducted during rain, heavy fog, or strong winds. Birds were caught passively and by field crews walking in a line across the subplot to flush birds into the net array at regular intervals throughout the netting period.

Mark-recapture data from systematic surveys were augmented by targeted mist-netting of adult birds at nests at all study sites; by banding nestlings shortly before they fledge from nests that we were monitoring; by mist-netting birds during spring and fall migration at our Connecticut sites; and by captures of birds at migration and wintering sites south of our main study area (Borowske 2015). Because the present analyses are focused on apparent survival of adults (second year or older), we only used capture-recapture data from individuals after they were caught as adults, as first year individuals likely have different rates of mortality and/or dispersal (cf. DiQuinzio et al. 2001). Some individuals caught on study plots as adults may have been captured previously during migration or as nestlings; however, this subset comprises less than 5% of our total dataset.

We fitted captured birds with United States Geological Survey-issued aluminum bands and a site-specific color band. We aged each individual based on plumage, and determined the sex by looking for a brood patch or cloacal protuberance. All birds were measured, scored for body condition and plumage features, and released.

Statistical methods

We estimated apparent annual survival of adults using the complete-data likelihood of Cormack-Jolly-Seber (CJS) models (Lebreton 1992; Schofield et al. 2009; Reed et al. 2014). Like other CJS models, the complete-data likelihood approach accounts for imperfect detection of marked individuals by using estimates of capture probability (p) to correct estimates of apparent survival (S). The complete-data likelihood approach allows one to include latent variables and encounter data obtained outside of the primary sampling scheme, potentially improving parameter estimation. For more details on the advantages of the approach, see Schofield et al. (2009) and Reed et al. (2014).

Table 30. Demography study sites at which mark-recapture data for tidal marsh sparrows were collected, 2010-2014.

Lat.	Long.	Marsh complex name	No. of Indiv. SALS banded ¹	No. of indiv. HYBRID banded	No. of indiv. NESP banded	No. of indiv. SESP banded	Plot size (ha)	Years
39.5059	-74.4256	Oyster Creek	178	0	0	373	19	2011-14
39.5355	-74.4425	Mullica Wilderness	372	0	0	132	17	2011-14
39.6969	-74.2112	ATT	377	0	0	97	14	2011-14
40.5997	-73.9072	Four Sparrow Marsh	22	0	0	2	1	2012-14
40.6084	-74.1927	Sawmill Creek	54	0	0	6	4	2012-14
40.6201	-73.6212	Marine Nature Study Area	39	0	0	2	4	2012-14
40.6518	-73.7515	Idlewild	64	0	0	133	3	2012-14
41.2621	-72.5520	Hammonasset	442	0	0	64	13	2010-14
41.2694	-72.6516	East River	379	0	0	81	19	2010-14
41.3055	-72.1066	Waterford	30	0	0	0	3	2011-13
41.3170	-72.2117	Pattagansett	42	0	0	1	8	2011-13
41.3370	-71.8703	Barn Island	253	0	0	66	23	2010-14
41.4425	-71.4657	John H. Chaffee NWR	94	0	0	0	12	2011-14
41.4872	-71.2491	Sachuest Point NWR	80	0	0	0	4	2011-14
42.7755	-70.8081	Parker River NWR	307	0	2	0	28	2013-14
43.0391	-70.9269	Chapman's Landing	287	19	36	0	12	2011-14
43.0754	-70.9153	LubberlandCreek	97	0	7	0	8	2012-14
43.2936	-70.5762	Eldridge Marsh	218	29	65	0	11	2011-14
43.5397	-70.3544	Jones Creek	285	204	55	0	17	2012-14
43.5539	-70.3284	Nonesuch River	87	82	77	0	14	2011-14
43.5632	-70.3584	Scarborough Marsh	236	195	113	0	10	2011-14

¹ Number of unique individuals captured at each study site is given for Saltmarsh Sparrow (SALS), Saltmarsh x Nelson's Sparrow hybrids (HYBRID), Nelson's Sparrow (NESP) and Seaside Sparrow (SESP).

We modeled systematic variation in both S and p using logistic regression. We modeled variation in S using sex (male = 1), marsh complex size, latitude, and random year and site effects. We modeled variation in p using sex (male = 1), study plot size, and the research institution overseeing a site. Plot size was included to account for any differences in capture rate caused by differences in the amount of area that was being surveyed and institution was included to account for minor variations in methods among field teams (all field teams used a common set of field protocols and were in constant communication throughout the project, but we recognize that small differences remain inevitable). We identified influential variables by constructing a normally-distributed prior distribution on the independent variables that was centered on zero and has a variance that was estimated by the model (cf. Gelman et al. 2004). This prior represents the knowledge that most independent variables have a small effect (potentially zero) on the response variables, but a few could have a large effect. The estimate of the variance parameter gives a measure of how important the modeled group of variables is

likely to be. The posterior distributions of the regression coefficients for each independent variable include the uncertainty associated with estimating the effect of all other variables, and can be examined directly to test how likely it is that the coefficient is non-zero. We report 95% credible intervals for each coefficient. Similarly, we assessed the relative importance of the random effects by plotting the posterior distributions of the variance parameters to see whether they were strongly non-zero.

We ran one model for Seaside Sparrows and another for Saltmarsh and Nelson's combined. Saltmarsh and Nelson's sparrows cannot always be positively identified in the field, creating a subset of unknown-species individuals from their hybrid zone, which extends from northern Massachusetts into Maine (Walsh et al. 2015). Ignoring this subset has the potential to bias estimates of apparent survival, in the same way that ignoring unknown-sex individuals can create biases (cf. Nichols et al. 2004). To avoid this bias, for birds caught in the hybrid zone we used a two-step process to 1) reduce the size of the unknown subset using linear discriminant function analysis (LDA) and 2) explicitly incorporate uncertainty for individuals that could not be assigned by the LDA. Walsh et al. (2015) created an LDA that assigns species to a "Saltmarsh" group and a "Nelson's" group based on measurements taken on every individual: wing chord, weight, and tarsus length. Using molecular methods, however, Walsh et al. (2015) found that it was not possible to distinguish hybrid backcrosses reliably from members of their parental species using structural or plumage metrics. Consequently, we took a conservative approach to assigning individuals to avoid bias from misclassification: individuals were only assigned with certainty if their LDA value fell within the range that had no misclassifications. We coded the remaining individuals as being of uncertain identity and used a Bayesian approach that explicitly incorporates uncertainty in species identification. Our approach is based on Schofield et al.'s (2009) method for dealing with covariate uncertainty. Species identification is treated as a Bernoulli random variable with p_i being the prior probability of an unknown individual belonging to the Saltmarsh group:

Eq. 1: $\text{species} \sim \text{Bernoulli}(p_i)$

p_i is defined as the proportion of Saltmarsh-group individuals in the hybrid zone, 0.69 (Walsh et al. 2015). The species identity of all individuals outside of the hybrid zone was treated as known. Unknown-species individuals were assigned to a species group for each step of the MCMC algorithm with a frequency determined by the prior, p_i , and the model likelihood, according to Bayes' theorem. An indicator variable was included in the model code to select the appropriate species-specific variables depending on the value of species_i for individual i at each step in the MCMC algorithm.

Results

For all species, models that had both site and year random effects for S did not converge. Site had a slightly stronger effect on S individually than did year (Figs. 19 and 20) and was of greater inferential interest. Accordingly, we report results from models with site effects, although results were essentially the same regardless of whether we included site effects, year effects, or neither.

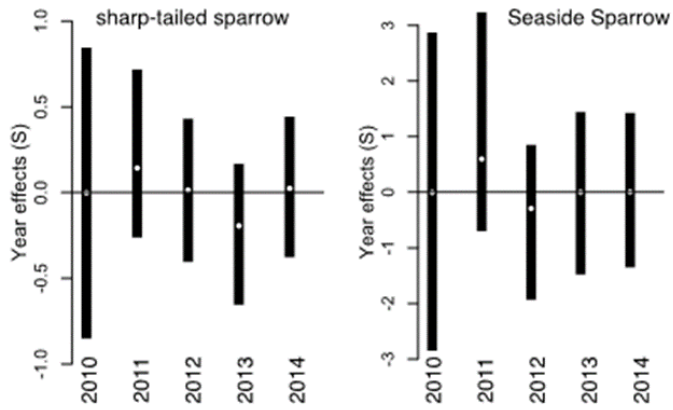


Figure 19. Year effects on “sharp-tailed sparrow” (data for Saltmarsh and Nelson’s were analyzed simultaneously to account for hybridization, see text for details) and Seaside Sparrow survival. White dots are means and black bars are 95% credible intervals. The overlap between bars suggests no differences in survival across years.

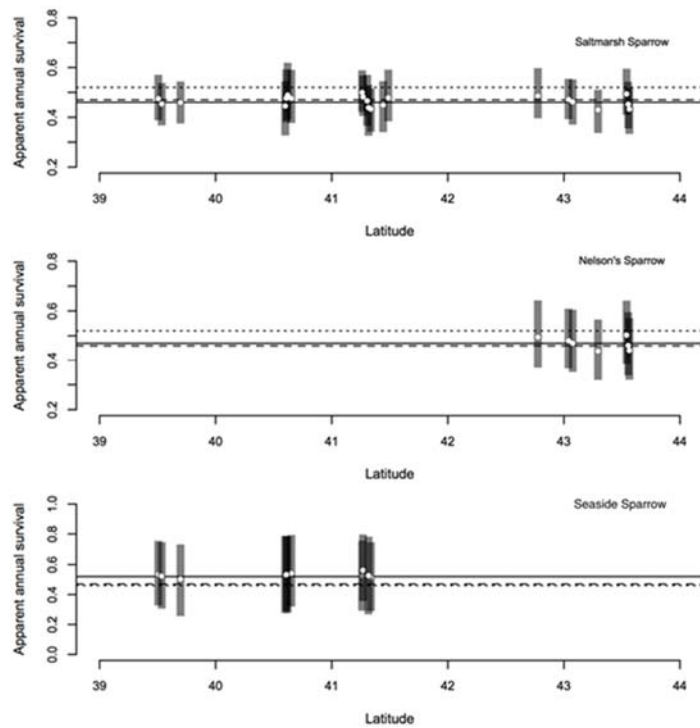


Figure 20. Apparent annual survival of female Saltmarsh, Nelson’s, and Seaside sparrows by latitude. Survival of females is shown; males have the same site effects but have slightly different mean survival (higher for Saltmarsh and Seaside, lower for Nelson’s) with credible intervals that are largely overlapping with females. White dots are means and black bars are 95% credible intervals. Solid horizontal line is for an average site. Average female survival for Seaside Sparrows (short dashes on top and middle panel), Nelson’s sparrow (long dashes on top and bottom panel), and Saltmarsh Sparrow (long dashes on the middle panel; short dashes on the bottom panel) are also shown. The overlap between bars suggests no site differences in survival for all three species.

All of the fixed effects, except the sex effect on p for the Saltmarsh group, had 95% credible intervals that overlapped zero (Fig. 21) indicating that they affected neither survival nor detection. For Saltmarsh-group birds, detection of males was lower than that for females. Effect sizes of predictors were essentially the same regardless of whether we included site effects, year effects, or neither. We found evidence for higher than average capture probability for “sharp-tailed” sparrows related to the research institution overseeing one site (i.e., the posterior distribution of that institution’s effect lies above 0), but there was no evidence for differences among institutions, potentially due to limited precision of institution effects (the credible intervals of individual effects overlap; Fig. 22); no similar effect was found for Seaside Sparrows.

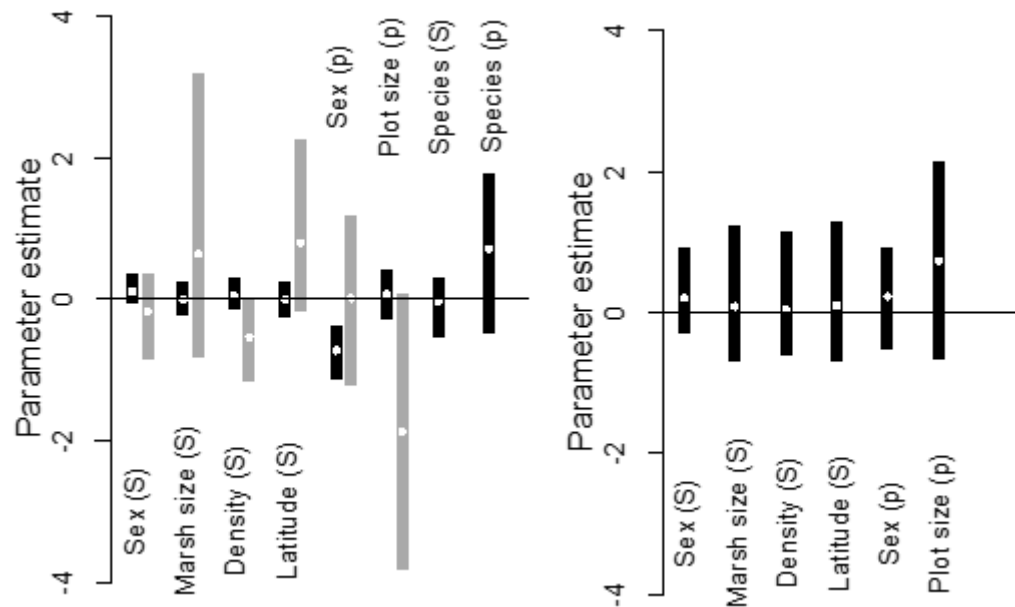


Figure 21. Left panel: Effect sizes for survival (S) and detection (p) for Saltmarsh and Nelson’s Sparrow, as derived from a combined model for both species. White dots are means, black bars are 95% credible intervals for Saltmarsh Sparrow, and gray bars are for Nelson’s Sparrow. Bars represents the effects of the named variables. Credible intervals for all bars include zero suggesting no effects, except for the sex effect on detection in Saltmarsh Sparrow. Two rightmost bars provide estimates for species effects, which were not found. Right panel: Effect sizes for Seaside Sparrow. White dots are means, black bars are 95% credible intervals.

Female Saltmarsh Sparrow survival at an average site was 0.46 (credible interval: 0.41, 0.51); male survival was 0.49 (0.44, 0.55). Apparent survival for female (0.47; 0.37, 0.59) and male (0.43; 0.26, 0.59) Nelson’s Sparrows were not significantly different from the equivalent rates for Saltmarsh Sparrows. Apparent survival of Seaside Sparrows was 0.52 (0.37, 0.71) for females and 0.57 (0.44, 0.75) for males.

Conclusions

Adult survival rates obtained during this study were similar among the three species and typical of those found in other species of North American sparrow (DeSante et al. 2015). Our overall estimate of survival for Seaside Sparrows was higher than for the two other species, but the credible intervals for all three species overlapped considerably. Although we have only four years of data for most of our sites, the

uncertainty around our point estimates is not especially large, suggesting reasonable confidence in our use of these numbers for population modelling (see section VIII, below). Nonetheless, we consider it important to continue monitoring our banded populations into the future in order to improve estimates further and better characterize annual variation in survival. Survival rates for all three species were similar across all sites and showed no clear evidence of latitudinal or other geographic patterns.

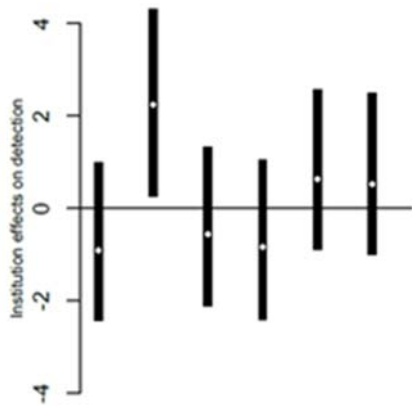


Figure 22. The effects of six research institutions on “sharp-tailed” sparrow capture rates. White dots are means and black bars are 95% credible intervals. One institution had higher capture rates than the overall mean, but there was overlap in credible intervals among all institutions suggesting no strong differences.

VIII. Sparrow Population Viability Analysis

Methods

For Saltmarsh, Seaside, and Nelson's sparrow, we created individual-based population models that propagate uncertainty from both parameter estimation and demographic stochasticity. A conceptual diagram of how uncertainty was accounted for is given in Fig 23. First, we drew values for the

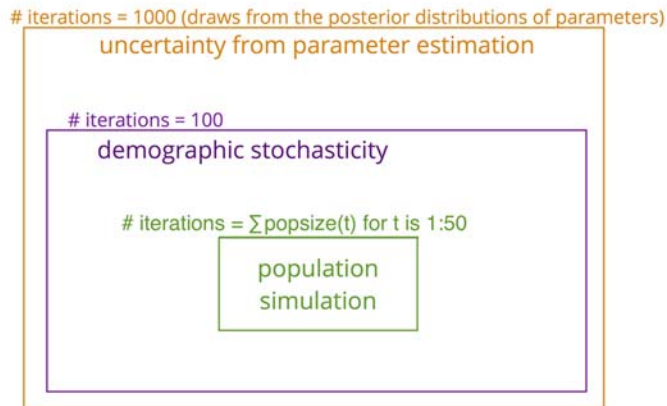


Figure 23. Conceptual model of population simulations. Demographic parameters are sampled from their posterior distributions 1000 times to account for estimation uncertainty. For each of these draws, 100 populations using the sampled values for the demographic parameters are simulated over 50 years. Using this method, the extinction risk estimates include uncertainty from both demographic stochasticity and uncertainty in estimating demographic parameters.

demographic parameters from their posterior distributions (taken from analyses of data described above, see sections VI and VII; we assumed that fecundity and survival parameters were not correlated in any given year). Using this set of demographic parameters, we simulated replicate populations (100 for each site for Saltmarsh Sparrow; 100 for each state for Seaside and Nelson's Sparrow, for which we had smaller sample sizes) for 50 years starting in 2013. A single replicate population is represented by the green box in Fig 23. The variation in growth rates among the replicate populations gives a measure of the demographic stochasticity for the current set of demographic parameters (represented by the purple box in Fig. 23). Second, we drew new values for the demographic parameters from their posterior distributions and simulated replicate populations as described above. We

repeated this process for 1000 draws of demographic parameters (represented by the orange box in Fig. 23) to represent variation from the estimation uncertainty of our survival and fecundity analyses described above.

All simulations modelled only females because the number of females is most critical to the demography of these species, especially Saltmarsh Sparrow, which has a sex ratio that is heavily skewed toward males (Hill et al. 2013). We took starting population sizes from Wiest et al. (in review; see section IV above) and assumed a 1:1 sex ratio for Seaside and Nelson's Sparrow and a 2:1 sex ratio for Saltmarsh Sparrow.

The demographic parameters used for Seaside and Nelson's sparrows were annual survival, first year survival (assumed to be 50% of annual survival), number of broods per season, and average brood size. For Saltmarsh Sparrow, our larger data set enabled us to separate the different components of fecundity more finely, which allows for more realistic estimates of uncertainty. This finer resolution also potentially results in more accurate estimates of extinction risk, as we were able to model certain parameters by latitude, date, and year, while also incorporating individual variation. This extra complexity was considered especially important because preliminary modeling suggested that the global

population could be threatened with extinction in the short term. We also had sufficient data to estimate Saltmarsh Sparrow fecundity and survival parameters at each demographic plot, enabling site-specific estimations of population growth rates across the species' geographic range. The demographic parameters used for Saltmarsh Sparrow include adult annual survival (as described above in section VII), first year survival (taken from a normal distribution assumed to have a 95% confidence interval that

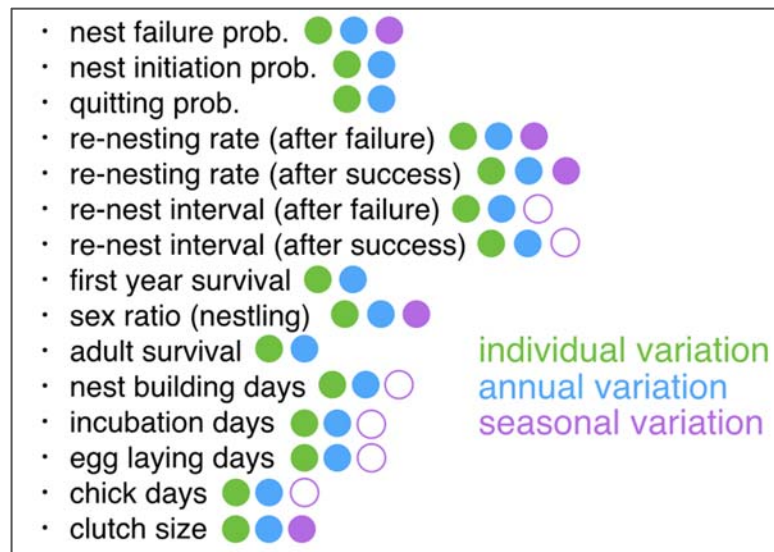


Figure 24. Demographic parameters for Saltmarsh Sparrow models and whether they are allowed to vary by individual (green), year (blue), and/or within a season (purple). Dots are filled in if the parameter has the associated variation built in. All of the parameters, except those that are intervals (to cut down on computation time), are allowed to vary by individual, year, and season.

ranged from 25-75% of adult survival), and the parameters used for fecundity estimation (see section VI): days until first nest initiation (since the first egg date for that site), re-nesting rates after success and failure, days between nesting attempts after success and failure, daily nest failure probabilities, clutch size, brood size, and quitting probability. For Saltmarsh Sparrows, most of these parameters were allowed to vary by individual, year, and/or across the season to create as much realism in the simulations as possible (Fig. 24). To estimate global extinction risk for Saltmarsh Sparrows, we also ran a model treating the population as a single panmictic population (starting population size of 25,800 females based on information in section IV).

Sea-level rise and habitat loss scenarios

The amount of future habitat that is suitable for nesting depends on both the rates of sea-level rise and sediment accretion. Various models exist for portions of our study area to project how habitats will change in the future (e.g., SLAMM), but none cover the entire region, uncertainty over accretion rates remains high, and none have been rigorously tested against field data. Moreover, the demographic impact of sea-level rise is largely mediated in the near term through the flooding of nests. Consequently, we modelled the effects of sea-level rise directly by increasing the daily nest failure rates commensurate with different relative sea-level rise scenarios.

We ran models for three scenarios. Our worst case scenario assumed no accretion and accelerating sea-level rise using global estimates from Vermeer and Rahmstorf (2009) that assume an IPCC A1F1 warming scenario. Our best case scenario assumed that accretion keeps up with sea-level rise, leading to no relative sea-level rise. Finally, our intermediate scenario assumed no accretion, but used linear rates of sea-level rise based on regional estimates from Boon et al. (2012). For each scenario we assumed the mean high tide would increase according to the projected rate of relative sea-level rise.

All of these scenarios are likely to be conservative because they assume that differences among sites with different mean high water or tidal exceedance probabilities mimic the long-term effects of sea-level change. Since, the effects of these variables in the contemporary data are small (Ruskin et al. in review; see section VI above), sea-level rise has only a small effect on model trajectories. In reality, we might expect sea-level rise to have more severe threshold effects on reproductive success, as has been found with a longer time series of nesting data from Connecticut (Elphick and Field, unpublished data). Additionally, our models include an effect on nest failure only and assume no effects on any of the other model parameters. Qualitative patterns of population growth were not very sensitive to the sea-level rise scenario used (see below) and we report only projections using the intermediate scenario of linear rise and no accretion.

For each species, we calculated the amount of habitat area in each state required for persistence by 1) determining the required starting population size for a 50% change in persistence over the next 50 years and 2) using density estimates from Wiest et al. (in review; see section IV above) to estimate the amount of habitat required to support a population of that size. For each species, we calculated the amount of habitat area in each state required for persistence by 1) determining the required starting population size for a 50% change in persistence over the next 50 years and 2) using statewide density estimates from Wiest (2015 (see section IV above) to estimate the amount of habitat required to support a population of that size.

Results

Differences in estimated population growth rates between the worst case and intermediate scenarios were all within the estimation error of our models, which was ~1% for growth rate estimates. This similarity arose because sea-level rise acceleration is minimal over the next 50 years. The best case scenario, which has no net sea-level rise, has consistent growth rates over time that are equal to those from the first five years of the other two scenarios (e.g., left panel of Fig. 25). Although, this scenario is better than the others, the consequences are minor because we found that the tidal variables used to estimate the sea-level effect have only small effects on nest failure rates (Ruskin et al. in review; see section VI above) and were assumed not to affect other variables.

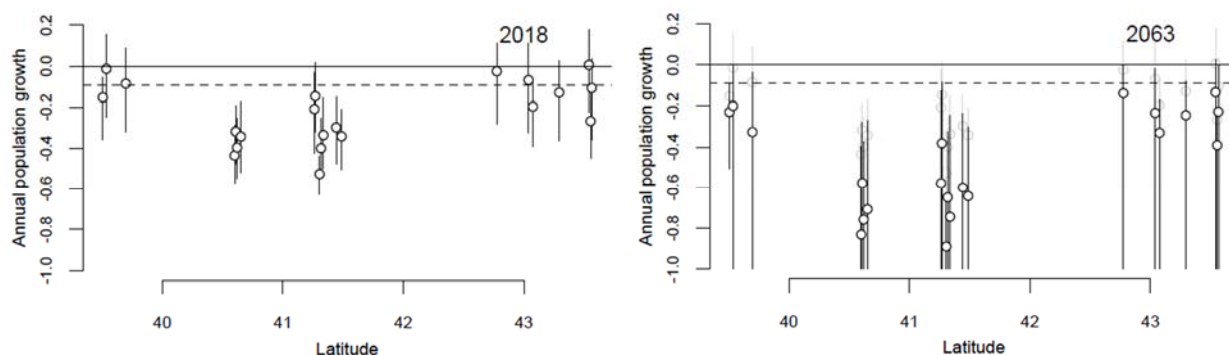


Figure 25. Saltmarsh Sparrow growth rates at 21 demographic plots, by latitude. White circles are mean estimates and black bars are 95% confidence. Left panel = growth rates for 2013-2018. Right panel = growth rates for 2058-2063, with 2013-2018 growth rates shown in pale gray for comparison (see Table 30 for more details on individual plots).

We estimated that, based on vital rates over the course of this study, mean growth rates for Saltmarsh Sparrows over the next five years will be negative at all of our demographic plots and that only eight out of 21 plots have 95% confidence intervals that overlap zero (Fig. 25, Table 31). By 2063, only one site will have a 95% confidence interval that includes positive growth rates (Fig. 25). Assuming that our demographic plots are representative of the species range, only ~5% of sites will have positive growth over the next 50 years (Fig. 26).

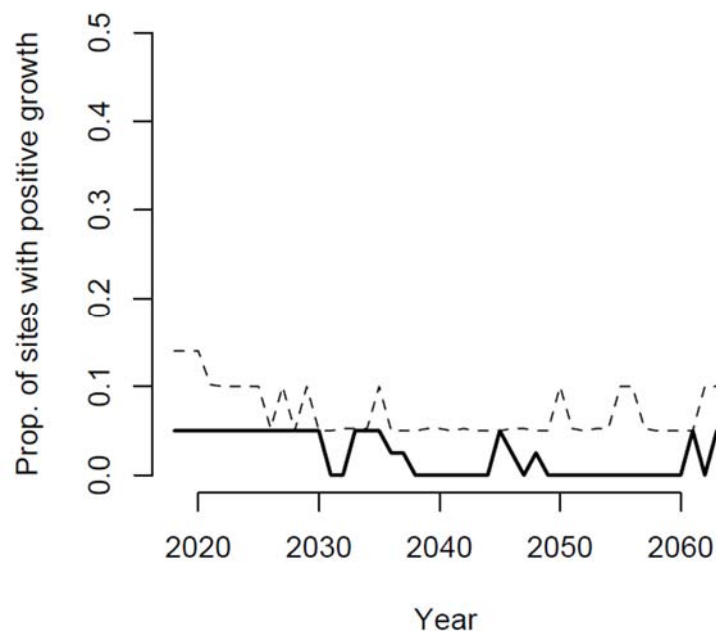


Figure 26. Estimated proportion of sites in the Saltmarsh Sparrow range with positive population growth. The black line is the mean and the dotted line is the upper 95% confidence interval. The lower bound of the interval, which is at zero for the entire period, is left off for clarity.

Global extinction risk for Saltmarsh Sparrow over the next 50 years is less than 5%. Although the global population can persist over this time frame, the population is expected to decline by 92% (95% confidence interval: 7 – 100%), putting the species on a clear trajectory towards extinction. If individual states are to ensure a 50% chance of avoiding Saltmarsh Sparrow extirpation over the next 50 years, then they will need to ensure a statewide population that includes at least 7,500 females. Of the states for which we have demographic data, only New Jersey currently has a population this large, and most states will need considerably more than their current marsh area in order to support such a large population (Table 32).

Our estimates suggest that Maine's Nelson's Sparrow population is likely not viable in the long-term without

immigration from other regions (80% chance of extinction within 50 years; Fig. 27, Table 33). For New Hampshire, extinction risk is less than 50% if the starting female population size is 100 individuals. This higher persistence probability for New Hampshire arises because of higher estimated fecundity than in Maine. It is worth noting, however, that a high proportion of "Nelson's-group" birds in New Hampshire are likely to be hybrids (Walsh et al. 2015).

We found minimal risk of extinction over the next 50 years for Seaside Sparrows south of Connecticut, but we estimate that there is an ~50% chance of being extirpated from Connecticut over the next 50 years (Fig. 27, Table 33). Although we lack data on Seaside Sparrow for states farther north, it is likely that their small populations would also go extinct. In order to reduce the extinction risk in Connecticut to less than 50%, the starting population size would need to be increased to 5000 females, considerably higher than the current population in southern New England (Weist 2015; see section VI, above). For New York and New Jersey, extinction risk is less than 25% if the female population size remains above 100 individuals.

Table 31. Estimated population growth rates and median time to extinction for Saltmarsh Sparrows at each demographic study site. Time to extinction estimates assume no immigration from other sites.

Marsh complex name	Mean growth rate in 2018	Lower 95% CI	Upper 95% CI	Mean growth rate in 2063	Lower 95% CI	Upper 95% CI	Median time to extinction (years)*	Lower 95% CI	Upper 95% CI
Oyster Creek	-0.15	-0.36	-0.056	-0.23	-0.51	-0.091	50+	50+	50+
Mullica Wilderness	-0.013	-0.25	0.15	-0.20	-1	0.0024	50+	46	50+
ATT	-0.085	-0.32	0.090	-0.33	-1	-0.036	50+	13	50+
Four Sparrow Marsh	-0.43	-0.57	-0.29	-0.83	-1	-0.40	9	2	35
Sawmill Creek	-0.32	-0.47	-0.19	-0.58	-1	-0.28	23	4	50+
Marine Nature Study Area	-0.40	-0.55	-0.25	-0.76	-1	-0.37	12	3	49
Idlewild	-0.34	-0.52	-0.17	-0.71	-1	-0.27	14	4	45
Hammonasset	-0.21	-0.42	-0.029	-0.58	-1	-0.12	27	9	50+
East River	-0.15	-0.32	0.016	-0.38	-1	-0.086	50+	13	50+
Waterford	-0.52	-0.63	-0.44	-0.89	-1	-0.63	6	4	31
Pattagansett	-0.40	-0.53	-0.25	-0.64	-1	-0.33	13	2	50+
Barn Island WMA	-0.33	-0.50	-0.15	-0.74	-1	-0.24	14	4	46
John H Chaffee NWR	-0.30	-0.47	-0.15	-0.60	-1	-0.24	22	6	50+
Sachuest Point NWR	-0.34	-0.50	-0.21	-0.64	-1	-0.30	18	4	50+
Parker River NWR	-0.025	-0.28	0.11	-0.14	-1	0.00007	50+	50+	50+
Chapmans Landing	-0.068	-0.32	0.11	-0.23	-1	-0.017	50+	27	50+
Lubberland Creek	-0.20	-0.39	-0.063	-0.33	-1	-0.017	50+	12	50+
Eldridge Marsh	-0.13	-0.36	0.026	-0.24	-1	-0.080	50+	50+	50+
Jones Creek	0.0059	-0.22	0.18	-0.13	-1	-0.026	50+	50+	50+
Nonesuch River	-0.22	-0.45	-0.13	-0.39	-1	-0.22	50+	6	50+
Scarborough Marsh	-0.11	-0.36	0.037	-0.23	-1	-0.0013	50+	50+	50+

Table 32. The amount of habitat required for a 50% probability of persistence for Saltmarsh, Nelson's and Seaside sparrows in individual states. There were no realistic scenarios for protecting viable populations of Nelson's Sparrow in Maine.

State	Population target (females) for 50% probability of persistence	Area (ha) of marsh required for persistence	% of state's current marsh area
<u>Saltmarsh Sparrow</u>			
NJ	7,500	59,324	72
NY	7,500	29,098	260
CT	7,500	46,364	941
RI	7,500	22,450	1,660
MA	7,500	40,502	230
NH	7,500	44,875	1,382
ME	7,500	84,405	925
<u>Nelson's Sparrow</u>			
NH	100	208	6
ME	NA	NA	NA
<u>Seaside Sparrow</u>			
NJ	100	115	1
NY	100	213	2
CT	5,000	11,905	241

Conclusions

Although our results suggest that Saltmarsh Sparrow populations are unlikely to go extinct within the next 50 years, the finding that they will have positive growth at only ~5% of sites over that period is alarming. Although Saltmarsh Sparrow is recognized as globally vulnerable with extinction by the IUCN and is considered a SGCN in many states, it is not currently afforded special protection in the USA (e.g., under the US Endangered Species Act). Our results suggest that the species may disappear from many of our study sites, most of which are located in well protected areas and were chosen because they have good habitat and relatively large populations, and much of its current range within the next few decades.

Like all models, our viability analyses make a number of assumptions and are subject to certain data limitations. In particular, the lack of long-term data for vital rates suggests that we may underestimate risk (cf. Reed et al. 2003). Moreover, throughout our model development we aimed to err in the

direction of conservative decisions so as not to overestimate extinction risk. Finally, our demographic data do not come from randomly selected study sites. When choosing sites for the collection of demographic data, we selected marshes known to support relatively high densities and to have apparently high quality habitat, in order to ensure that we were able to obtain large samples for estimating reproduction and survival rates. It is quite likely, therefore, that our data represent some of the best sites for tidal marsh sparrows within each state. If this is true, then it would further suggest that our results are conservative and that extinction risk is higher than our current models suggest. None of our models account for immigration into populations, which has not been rigorously quantified, and immigration could, theoretically, increase the chance of persistence at some sites. Given how widespread the projected declines are, however, it is unlikely that there will be substantial source populations or that immigration will make a substantial difference. New work has begun to evaluate some of these issues, to collect additional data, and to develop a new generation of models that will test the importance of these concerns.

Given the small area of tidal marsh in any one state, and the fact that most states lack sufficient habitat to ensure long-term viability of Saltmarsh Sparrow populations, is it important that conservation planning take place at a larger spatial scale. Although we lack such detailed demographic analyses for other tidal marsh birds, our results for Seaside and Nelson's sparrows suggest that such coordination is likely to be important for these species as well. Indeed, the small total area of tidal marsh habitats and the consistent pattern of decline for tidal marsh specialists (see section V above), suggests that the same coordinated conservation planning is needed for the entire avian community (see section IX, below)

Table 33. Estimated population growth rates and median time to extinction for Seaside and Nelson's sparrows in each state for which we have demographic data. Time to extinction estimates assume no immigration from other states. NA indicates that a state is outside of the species' primary breeding range.

State	Seaside Sparrow			Nelson's Sparrow		
	Median time to extinction (years)	Lower 95% CI	Upper 95% CI	Median time to extinction (years)	Lower 95% CI	Upper 95% CI
New Jersey	50+	45	50+	NA	NA	NA
New York	48	20	50+	NA	NA	NA
Connecticut	38	16	50+	NA	NA	NA
New Hampshire	NA	NA	NA	50+	42	50+
Maine	NA	NA	NA	30	15	50+

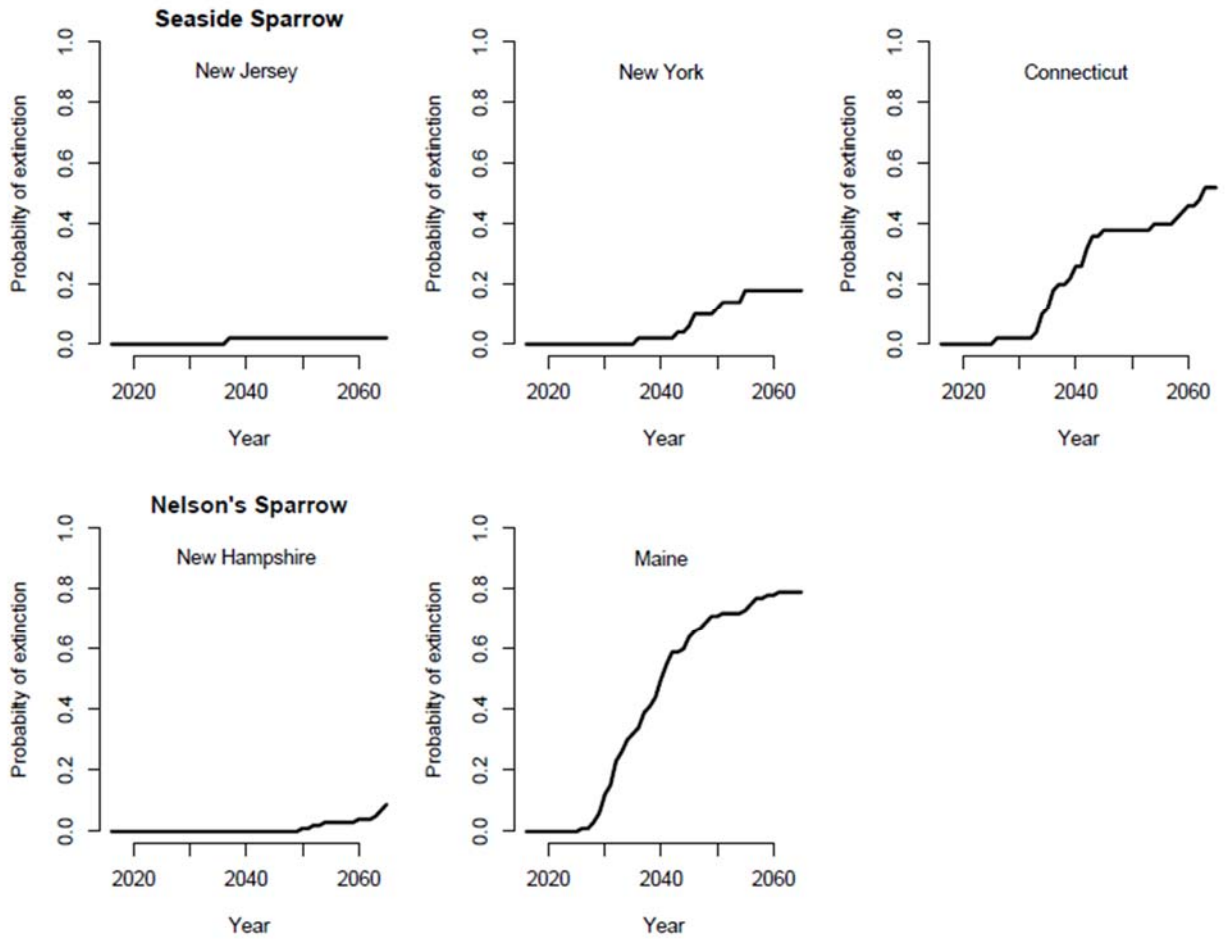


Figure 27. Probability of extinction, by state, for Seaside and Nelson's Sparrow. Extinction risk was calculated taking into account both parameter estimation uncertainty and demographic stochasticity.

IX. Decision Support Tools

Delaware case study (see Appendix C for complete report)

To prepare for the challenges tidal marshes face from global climate change, conservation decisions must be made using objective, quantitative and repeatable methods that incorporate sea level rise uncertainties. Such decision-making should effectively prioritize land acquisitions and efficiently allocate limited conservation funds while proactively addressing potential future habitat changes. Two selection methods used by conservation planners to identify priority projects for land acquisition or easement opportunity vary in their capacity to select cost-effective projects given the fiscal constraints of limited budgets. Benefit targeting is a rank-based method that uses a “greedy agent” algorithm to acquire parcels with the highest conservation value, independent of project costs, until a specified budget is exhausted. These “greedy heuristic algorithms” are routinely used in conservation planning for reserve site selection and, given the availability of avian data, these taxa are well represented as a measure of the conservation benefit in reserve selection projects. Although benefit targeting continues to be the most used method for developing conservation planning strategies, the method’s outcomes can lead to inefficient monetary spending and suboptimal conservation gains. Alternative methods to benefit targeting include linear, binary, and mixed integer programming. These optimization algorithms find solutions that minimize the expenditure of financial resources while simultaneously maximizing a desired conservation target. Optimization algorithms are being used more frequently to answer a variety of conservation questions.

We tested these two approaches as a case study in Delaware to compare the site prioritization between benefit targeting and optimization and then determines the future persistence of the selected parcels given three sea level rise scenarios and the implications for the tidal marsh bird community. The specific objectives of this case study were to: 1) determine the tidal marsh areas in Delaware that support the greatest density of breeding tidal marsh obligate birds, 2) identify the extent of protected and unprotected salt marsh habitat in the state, 3) identify and compare benefit targeting- and optimization-selected parcel portfolios that maximize bird density on unprotected marsh habitat in three budget scenarios, and 4) determine the effect of three sea level rise scenarios on the proportion of land cover types within the optimized parcels.

We used three budget level scenarios, \$10M, \$15M, and \$20M, to develop budget specific parcel portfolios based on benefit targeting and optimization, and used tidal marsh obligate breeding bird density as our conservation target. We used three sea level rise scenarios (0.5 m, 1.0 m, 1.5 m) to estimate the land cover types that would remain within each selected parcel. The optimization method selected more parcels, protected more marsh area, and conserved more tidal marsh obligate birds, than the more traditional benefit targeting method. Total marsh area ranged from 7.2–9.6% greater and bird density ranged from 7.3–12.8% greater given the optimization method. When benefit targeting and optimization protected the same number of birds, optimization provided a cost savings of \$1.75M–\$2.9M. All sea level rise scenarios inundated greater than 95% of the wetland area on selected parcels. Agricultural land had the greatest amount of area remaining of any land cover type in all scenarios, ranging from 79.9 ha, 82.0% of total portfolio area (\$10M–1.5 m scenario), to 648.7 ha, 70.8% of total portfolio area (\$20M–0.5 m scenario). Optimization models can be used to develop comprehensive strategies that protect marshes with current core tidal marsh bird populations. Increasing rates of inundation from sea level rise, however, will likely lead to losses of existing wetland areas. The potential future benefits of adjacent agricultural lands to tidal marsh birds through marsh migration should be

incorporated into optimization models for more effective conservation planning and spending of limited financial resources

Connecticut case study (see Appendix D for complete report)

Conservation practitioners in Connecticut are beginning to invest resources in decision support tools (DSTs) that will guide them in making sense of the bewildering array of options for land protection and restoration, especially along the coastline. One such tool, currently being developed by Fountains Spatial, is intended to guide the Long Island Sound Stewardship site selection process. Further development of a wildlife complement to this tool is a high priority for several organizations, including the State Department of Energy and the Environment (DEEP), Audubon Connecticut, and the Connecticut Audubon Society. This report outlines a pilot DST to guide decisions for coastal bird conservation. At 2010's Connecticut "Avian Summit" – a meeting of representatives of most of the major organizations involved with bird conservation in the state – saltmarsh and beach-nesting birds were identified as a high conservation priority and, because data already exist for many species, a logical systems for which to develop a set of prototype DSTs. The prototype presented here is based on a systematic planning process (Margules and Pressey 2000). Following this science-based process will ensure that decisions based on the resulting tools are defensible, transparent, and based on the latest peer-reviewed evidence on how to make smart conservation decisions.

Saltmarsh and beach systems are complex, dynamic, and surrounded by uncertainty. Salt marshes in Connecticut are expected to undergo drastic changes in the next 100 years as sea levels continue to rise (Hoover 2010). One adaptation strategy, already being implemented by several conservation organizations, is to protect open space adjacent to salt marshes (often by purchasing the land outright) to create avenues for the potential landward migration of marshes. Because land prices in Connecticut are high, a successful implementation strategy will hinge on achieving efficiency in decision-making that will give the greatest conservation benefit per dollar spent. A challenge to achieving this efficiency is that land prices change with markets over time, and are not predictable with complete certainty. Therefore, the DST we have developed explicitly accounts for the uncertainty of how much it will cost to protect land, providing practitioners with the decision-making framework to make low-risk, high-efficiency decisions.

Setting targets

In-person meetings to discuss quantitative conservation targets were held in early 2010 at the Center for Environmental Science and Engineering at the University of Connecticut, and in early 2011 at a breakout session during the Connecticut Conference on Natural Resources. These sessions were followed by surveys in which conservation practitioners ranked salt marsh and beach-nesting birds and their habitats in order of conservation priority. Using the results of these surveys, we narrowed the list of conservation targets to 5 species and 2 habitat types (Table 1). For each of the targets on this priority list, we developed three alternatives for quantitative population or habitat-area targets, and used a second survey to determine which target was favored by the stakeholder group. DSTs were developed with the goal of protecting sufficient land to ensure that these quantitative targets are met. Given current population sizes, some targets are impossible to meet via protection alone, and will require

active management for population growth (e.g., habitat restoration or creation) if they are to be achieved.

For the prototype DST analysis, we focused on the two tidal marshes species, Saltmarsh Sparrows and Seaside Sparrow, and conducted analyses to address the following questions: (1) Are all of the marsh complexes for which comprehensive data exist needed to meet the target population sizes? (2) How much of the land at each of these marsh complexes is currently protected via land ownership or conservation easements? (3) Can land parcels at individual marshes be prioritized according to the trade off between conservation benefits versus economic cost of protection? Although beyond the scope of this contract, work on a DST focused on the beach-nesting priority species was also begun.

Data compilation

Sparrow abundance data were obtained from standardized point counts of tidal marsh birds (see Gjerdrum et al. 2008, Elphick et al. 2009, Meiman 2009). Land value data were compiled from the Town of Stonington's tax assessor and trulia.com. Additional data on beach-nesting birds were also compiled from the Connecticut DEEP's Piping Plover and Least Tern Recovery Project, although these were not used for the pilot tidal marsh DST.

Estimating priority bird species abundance

We analyzed the raw point count data using Bayesian hierarchical models to estimate marsh-level abundance of Saltmarsh and Seaside sparrows for six major marsh complexes: Milford area; East River, Guilford/Madison; Hammonasset, Madison; Lower Connecticut River; Bluff Point, Groton; and Barn Island, Stonington. For both species, the target statewide population size was within the estimated confidence intervals of the total population size for the 6 marsh complexes combined. This result suggests that these sites all need to be protected in order to meet the targets (Figure 1).

Current protected status of salt marshes

We determined the proportion of total marsh habitat in the six major marsh complexes that is under some kind of protected status (i.e., conservation easement or in conservation ownership) using DEEP's Connecticut Parcels for Protected Open Space Mapping (POSM) database and data from the U.S. Geological Survey's GAP analysis program (<http://gapanalysis.usgs.gov/>). For this initial analysis, we did not include land that is simply protected by the existence of wetland legislation. The protected status of Connecticut's marshes is variable, with Stonington's Barn Island closest to being fully protected (Figure 2).

Incorporating land costs

To help guide management decisions we developed a method for prioritizing land parcels based on the trade-off between their cost and their conservation benefits. We implemented this method for the marshes at Barn Island to illustrate the approach and demonstrate its utility. For each tax parcel in this marsh complex, we compiled two pieces of information: 1) the total area of high and low marsh, calculated using a raster developed by Hoover (2010) and 2) the assessed value of the property from the Town of Stonington's Tax Assessor. Because information from the assessor's office does not reflect the most up-to-date property values, we also conducted a regression-based economic analysis of recent land sales in Stonington using information from trulia.com. From these analyses we estimated that

Stonington's overall housing market has likely declined by ~30% since properties were last assessed, and that 95% of properties were sold within the range of $\pm 20\%$ of market value. By combining the assessed values with the estimated market change we were able to estimate both the current market value and uncertainty in that value (i.e., $\pm 20\%$) for each parcel.

Prioritization using the “fraction of the spares”

We determined that the “fraction of the spares” (FOS) conservation index (Phillips et al. 2011) was the most flexible way to identify which tax parcels were the highest priorities for acquisition. The FOS is conceptually simple and computationally inexpensive, which makes it possible to easily recalculate the index to keep up-to-date with changing land markets and the most recent conservation actions. We calculated the FOS for each parcel in the Barn Island complex, and ranked parcels according to their relative contributions to our targets based on the area of high and low marsh in each parcel. These values were then prorated by dividing the FOS value by the cost of purchasing the parcel, in effect turning the index into a cost/benefit ratio. This ratio was calculated for every parcel in Stonington that contained marsh habitat. The uncertainty of the likely sales price (represented by the $\pm 20\%$ interval around the market value) was propagated in the calculation of the index, resulting in FOS values with 95% confidence intervals.

Recommendations for region-wide expansion

Now working prototypes have been developed in both CT and DE, we anticipate that the next stages will be to extend the analysis to a region-wide scale and to incorporate predictions of future marsh distributions. Doing this would make it possible to prioritize purchase of land parcels in order to most efficiently ensure that marshes are capable of migrating landward (naturally or with assistance) in the long-term. Most of tidal marshes are currently protected by legislation for wetland protection, but potential areas for landward migration are not, and for the next several decades these sites will likely be the main focus of attention for saltmarsh conservation in the state.

Existing wetland conservation programs on private lands, such as the Wetlands Reserve Program (WRP) and Wildlife Habitat Incentives Program (WHIP), provide landowners with funding for technical and financial support for conservation projects and could provide opportunities for tidal marsh conservation in the future. Both programs are authorized through the U.S. Farm Bill (Food, Conservation, and Energy Act of 2008) and administered by the U.S. Department of Agriculture’s Natural Resources Conservation Service (NRCS). Through the WRP, landowners protect or enhance wetlands on their property, including restore wetlands from former agriculture fields, and may be reimbursed up to 100% of conservation easement costs (NRCS 2008). The program is best “suited for frequently flooded agricultural lands, where planned restoration will maximize habitat for migratory birds and other wildlife, and improve water quality” (NRCS undated a). WHIP assists landowners in creating priority fish and wildlife habitat through cost-share agreements and landowners may be reimbursed up to 90% of the costs (NRCS 2011). While the WRP and WHIP have been successful in creating and conserving habitat in and for the present, more incentives and long-term agreements are needed to bolster private landowners’ voluntary program participation to ensure the future existence of habitats and associated species.

Working Lands for Wildlife, a new partnership between NRCS and U.S. Fish and Wildlife Service announced in September 2012, directly addresses conservation for declining species on working agricultural lands and may be able to provide critical additional support for tidal marsh conservation in

the future. The program provides technical and financial assistance through WHIP to farmers, ranchers, and forest owners to reverse declining populations of seven specific wildlife species (i.e., Bog turtle, Gopher tortoise, New England cottontail, Greater sage-grouse, Lesser prairie chicken, Southwestern willow flycatcher, and Golden-winged warbler). Considering predictions for the future of tidal marshes, current avenues for wetland conservation will likely need to take on new dimensions to achieve conservation goals in the face of global climate change. Regardless of how conservation programs are supported, policies that provide opportunities for wetlands to migrate inland are likely to be less expensive and will have a greater probability of success if planning occurs before these lands are developed.

The approaches we have developed here are purposefully very flexible, easy to calculate and understand, and based on the latest research in conservation biology and decision theory. We have deliberately applied the approaches to simple examples with a small set of conservation targets and a single conservation action in order to illustrate the method as a “proof-of-concept”. Both approaches, however, can easily be expanded or applied to other systems by including a larger set of targets and considering a wider range of conservation actions (e.g., restoration), or even explicitly trading-off the costs and benefits of alternative conservation actions. It also would be possible to combine information from disparate areas of conservation (e.g., by examining the trade-offs between conservation actions for beach-nesting birds vs. tidal marsh birds). An additional extension of the current models would be to incorporate information on each parcel's vulnerability to development or ability for marshes to transgress into the optimization which would likely shift conservation priorities to those parcels that are likely to persist or become marshes in the future.

X. Future Directions

Data Storage and Maintenance

In spring 2015, SHARP entered into an agreement with Winning Solutions Inc. a professional database development and data management company (<https://www.winningsolutionsinc.com/>). The initial phase of this agreement was to normalize all SHARP avian and vegetation survey data 2011 – present into multi-year combined Microsoft SQL Server database; create a web based data entry input form to allow individuals to enter data into a web form and have it committed directly to the multi-year database; and create a Microsoft Access 2013 database with connections to all the SQL tables in the new database. The webbased interface was created using a framework called “Bootstrap” that enables the automatic scaling of the webpage from phone to desktop monitor size screens. <http://getbootstrap.com/>. Long-term data storage will occur on a SQL server located at the University of Maine and the SHARP Database will be linked directly off the SHARP webpage (www.tidalmarshbirds.org). All hard copy data (field forms) are photocopied, scanned as PDF, and stored with the USFWS Region 5 I&M data manager and at the University of Delaware.

Hurricane Sandy Studies

Following Hurricane Sandy, the data set produced by this project provided an unprecedented opportunity to investigate the effects of a major storm on coastal marshes, and on coastal resilience more generally. Using the data presented in this report as a platform, we have since received additional grants that are allowing us (a) to evaluate the effects of the storm using SWG-funded data as pre-storm baseline data and (b) to extend our sampling to quantify baseline conditions where post-storm

restoration work is being done. Additional work will be conducted to provide before- and after-restoration sampling at sites throughout the mid-Atlantic and New England states will be used to investigate the efficacy of different recovery actions. By pooling information from multiple restoration sites using a standardized set of survey protocols (all available at <http://www.tidalmarshbirds.org/>), our sampling will allow rigorous quantification of whether methods work, how they compare, and what they contribute to coastal resilience. We also participated in a 2014 multi-agency conference organized by the North Atlantic Landscape Conservation Cooperative at Hadley, MA, and a 2015 symposium at the Society for Wetland Scientists' conference in Providence, RI, both of which were intended to bring together a diversity of scientists working on storm impacts and coastal resilience.

Eastern Tidal Marsh Conservation Business Plan

As a result of this grant, we have convened three symposia at bird conservation and management meetings organized by Partners in Flight (PIF) in the eastern US (2010: Plymouth, MA; 2012: Plymouth, MA; 2014: Virginia Beach, VA) in order to keep stakeholders up to date on our work. The culmination of these symposia has been the convening of a group to develop an eastern North America tidal marsh conservation business plan under the National Fish and Wildlife Foundation's business planning model. In addition to the 2014 symposia, at the Virginia Beach PIF meeting we organized a special session focused on setting the scope for the plan, identifying focal species, and conducting a comprehensive threat assessment for the highest priority species. A follow-up meeting to identify action items, an implementation plan, and assessment metrics is planned for winter 2015-16. Details of the conservation plan's status are provided here: http://www.tidalmarshbirds.org/?page_id=1682. Details of the symposia we have held and a complete listing of the 125 presentations given by our group since the start of this project are provided here: http://www.tidalmarshbirds.org/?page_id=1414.

Future Research Needs

- A. Collaborate with identified investigators from the Southeastern US to implement a consistent platform for tidal marsh conservation from the Gulf of Mexico to the Gulf of Maine
- B. Develop sub-marsh-scale management techniques to maintain bird-suitable high marsh habitats in the face of sea-level rise (e.g., tree-cutting, tidal booms, floating islands, tide gate manipulation, runnel cutting)
- C. Experimentally test methods to convert marsh-adjacent agricultural lands into bird-suitable high marsh (To develop an NRCS program for adaptation to sea-level rise)
- D. Experimentally test the impacts of nutrient subsidies on the resilience of marshes to sea-level rise, and trace the landscape sources of such subsidies (To rank marshes at risk of eroded resilience and provide actions for increasing local marsh resilience)
- E. Determine the effects of dams and dam removal on tidal marsh bird community stability and resilience
- F. Quantify the ecosystem services of restored and unrestored marshes (and regional marsh complexes) using methods comparable to service estimators in other systems world-wide
- G. Expand our state-level decision-support tools to optimize tidal marsh conservation for the entire region, combining our biological knowledge with social science data and modeling
- H. Trial Saltmarsh Sparrow husbandry techniques to allow for the quick and successful development of a breeding program, should it become necessary

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XII. Appendices

Appendix A: Model Evaluation Tables from Bayes Net

Table B1. Model complexity, performance, and validation of the Bayesian network models predicting species occurrence as a function of patch covariates.

<i>Species Model</i> ^{a,b}	Spherical payoff	Model complexity		Model performance, confusion error rates, %			Model validation (5-fold), mean confusion error rates, mean %		
		No. covariates	No. probabilities	Absent	Present	Total ^c	Absent	Present	Total ^c
<i>Clapper rail</i>									
All 1	0.869	3	74	11.6	27.5	17.3	17.8	27.5	22.0
Sub 2	0.895	7	158	12.8	13.2	12.9	16.6	20.2	18.4
All 2	0.901	9	194	9.8	15.4	11.8	16.5	24.2	19.6
Sub 3*	0.905	11	230	10.4	14.3	11.8	13.2	20.9	16.5
All 3	0.916	15	296	8.5	14.3	10.6	10.7	31.0	18.4
Sub 4	0.910	16	338	8.5	14.3	10.6	11.5	25.5	16.5
All 4	0.918	22	832	9.8	11.0	10.2	16.7	30.5	21.2
<i>Willet</i>									
All 1	0.836	3	74	5.8	55.8	19.9	8.3	58.1	22.9
Sub 2	0.857	7	158	7.0	43.6	17.4	9.5	45.8	20.3

<i>Species</i> Model ^{a,b}	Spherical payoff	Model complexity		Model performance, confusion error rates, %			Model validation (5-fold), mean confusion error rates, mean %		
		No. covariates	No. probabilities	Absent	Present	Total ^c	Absent	Present	Total ^c
All 2	0.854	9	194	7.4	41.8	17.2	10.8	46.1	21.3
Sub 3	0.855	11	236	11.3	37.0	18.6	13.6	42.8	22.4
All 3	0.861	15	308	11.3	32.7	17.4	13.6	43.7	22.5
Sub 4	0.862	16	338	12.2	33.3	18.2	13.7	42.1	22.0
All 4*	0.895	22	1,156	10.6	19.4	13.1	13.9	40.6	21.8
<i>Nelson's sparrow</i>									
All 1	0.857	3	74	12.5	31.6	18.1	12.5	53.0	24.4
Sub 2	0.894	7	164	9.6	26.3	14.5	12.5	41.2	20.8
All 2	0.882	9	200	11.0	29.8	16.6	14.7	42.2	22.8
Sub 3	0.906	11	236	6.6	21.1	10.9	12.4	51.5	23.9
All 3*	0.905	15	308	7.4	19.3	10.9	11.9	46.0	21.8
Sub 4	0.906	16	270	6.6	21.1	10.9	11.0	51.2	22.8
All 4	0.898	22	336	6.6	28.1	13.0	12.5	41.0	20.8
<i>Saltmarsh sparrow</i>									
All 1	0.748	3	74	61.3	13.6	35.2	61.1	16.8	36.5
Sub 2	0.789	7	158	36.1	20.1	27.3	45.8	26.9	35.2

<i>Species</i> Model ^{a,b}	Spherical payoff	Model complexity		Model performance, confusion error rates, %			Model validation (5-fold), mean confusion error rates, mean %		
		No. covariates	No. probabilities	Absent	Present	Total ^c	Absent	Present	Total ^c
All 2	0.788	9	200	37.8	19.7	27.9	48.4	27.9	36.9
Sub 3	0.853	11	236	21.7	16.1	18.7	28.3	22.6	25.2
All 3	0.859	15	308	18.7	17.6	18.1	28.6	21.6	24.8
Sub 4	0.863	16	328	19.6	16.1	17.7	24.8	20.6	22.6
All 4*	0.917	22	1,194	13.9	7.9	10.6	18.3	13.8	15.9
<i>Seaside sparrow</i>									
All 1	0.805	3	74	9.7	63.4	26.7	18.5	59.3	32.1
Sub 2	0.832	7	164	12.4	39.8	21.0	15.3	47.7	26.2
All 2	0.838	9	194	10.9	38.2	19.5	15.9	52.9	28.2
Sub 3	0.849	11	230	11.2	35.0	18.7	14.5	43.1	23.8
All 3	0.853	15	296	13.5	30.1	18.7	16.9	41.8	25.4
Sub 4	0.881	16	344	12.0	22.8	15.4	14.5	31.0	20.3
All 4*	0.912	22	914	8.2	16.3	10.8	12.9	28.1	17.9

^a Number of cases in each species data set used to parameterize the models: clapper rail = 255, willet = 582, Nelson's sparrow = 193, saltmarsh sparrow = 509, and seaside sparrow = 390.

^b Final selected models are indicated by an '*'.

^cThe percent error of the absent and present states equals 100% of total error.

Table B2. Model complexity, performance, and validation of the Bayesian network models predicting species density (birds per ha) as a function of patch covariates.

Species Model ^{a,b}	Spherical payoff	Model complexity		Model performance, confusion error rates, %				Model validation (5-fold), mean confusion error rates, mean %			
		No. covariates	No. probabilities	0	>0 - 1	>1	Total ^c	0	>0 - 1	>1	Total ^c
Clapper rail											
All 1	0.822	3	111	8.5	40.8	85.0	23.5	14.7	38.1	100.0	28.6
Sub 2	0.863	7	237	10.4	21.1	55.0	16.9	14.9	32.1	71.7	25.5
All 2	0.872	9	291	9.8	25.4	50.0	17.3	15.5	37.9	91.7	28.2
Sub 3	0.875	11	336	9.1	23.9	25.0	14.5	14.5	38.7	65.0	25.9
All 3	0.900	15	444	8.5	22.5	15.0	15.5	10.6	40.8	63.3	25.1
Sub 4	0.890	16	498	8.5	25.4	15.0	13.7	13.8	36.7	65.0	25.1
All 4*	0.903	22	1,248	9.1	19.7	15.0	12.6	16.6	45.0	45.0	27.5
Willet											
All 1	0.809	3	111	5.0	55.0	97.8	22.5	7.6	56.1	100.0	24.9
Sub 2	0.834	7	237	5.5	48.3	73.3	19.6	8.3	57.1	89.5	24.9
All 2	0.826	9	291	8.6	52.5	62.2	21.8	8.6	58.2	90.8	25.3
Sub 3	0.835	11	345	8.9	49.2	64.4	21.5	12.0	63.2	86.0	28.4

<i>Species</i> Model ^{a,b}	Spherical payoff	Model complexity		Model performance, confusion error rates, %				Model validation (5-fold), mean confusion error rates, mean %			
		No. covariates	No. probabilities	0	>0 - 1	>1	Total ^c	0	>0 - 1	>1	Total ^c
All 3	0.841	15	453	11.5	40.8	44.4	20.1	12.2	61.0	82.9	27.7
Sub 4	0.833	16	507	11.8	42.5	51.1	21.1	14.9	57.2	80.2	28.7
All 4*	0.866	22	1,734	6.5	32.5	57.8	15.8	12.2	56.3	77.3	26.6
<i>Nelson's sparrow</i>											
All 1	0.815	3	111	5.9	55.9	82.6	23.8	10.3	65.3	92.7	30.0
Sub 2	0.866	7	255	7.4	41.2	47.8	18.1	14.0	70.3	84.7	32.6
All 2	0.870	9	300	7.4	29.4	43.5	15.5	13.2	67.3	75.7	30.6
Sub 3	0.888	11	354	5.1	26.5	34.8	12.4	12.4	74.7	84.3	32.1
All 3	0.906	15	471	5.1	17.6	34.8	10.9	8.8	66.0	87.7	28.5
Sub 4	0.901	16	414	5.1	20.6	34.8	11.4	9.5	74.0	84.3	30.0
All 4*	0.898	22	531	5.1	23.5	30.4	11.4	8.1	70.0	79.3	27.5
<i>Saltmarsh sparrow</i>											
All 1	0.708	3	111	57.0	17.9	100.0	39.9	60.2	21.0	100.0	42.6
Sub 2	0.753	7	246	37.0	23.4	81.5	32.6	48.6	29.7	95.0	41.7
All 2	0.755	9	300	37.0	24.2	77.8	32.8	44.7	34.1	100.0	42.1
Sub 3	0.820	11	345	19.6	21.4	59.3	22.6	29.1	27.5	92.1	31.8

<i>Species</i> Model ^{a,b}	Spherical payoff	Model complexity		Model performance, confusion error rates, %				Model validation (5-fold), mean confusion error rates, mean %			
		No. covariates	No. probabilities	0	>0 - 1	>1	Total ^c	0	>0 - 1	>1	Total ^c
All 3	0.832	15	453	18.7	22.2	54.5	21.8	28.5	26.8	92.1	31.0
Sub 4	0.834	16	492	19.6	20.6	48.1	21.6	24.5	28.3	97.1	30.3
All 4*	0.895	22	1,815	12.6	11.9	22.2	12.8	19.8	18.8	94.3	23.2
<i>Seaside sparrow</i>											
All 1	0.773	3	111	8.2	84.8	58.1	30.3	9.7	85.9	79.6	33.8
Sub 2	0.811	7	246	13.9	59.8	29.0	25.9	14.6	69.8	50.9	31.0
All 2	0.812	9	291	11.6	62.0	29.0	24.9	14.1	68.5	52.5	30.5
Sub 3	0.830	11	345	11.2	55.4	19.4	22.3	14.8	69.2	53.0	31.0
All 3	0.836	15	444	11.2	50.0	12.9	20.5	15.8	61.2	58.7	30.8
Sub 4*	0.862	16	528	10.1	34.8	19.4	16.7	15.7	55.7	46.8	28.2
All 4	0.903	22	1,365	6.4	26.1	12.9	11.5	10.3	46.2	62.7	23.1

^a Number of cases in each species data set used to parameterize the models: clapper rail = 255, willet = 582, Nelson's sparrow = 193, saltmarsh sparrow = 509, and seaside sparrow = 390.

^b Final selected models are indicted by an '*'.

^c The percent error of the three density states equals 100% of total error.

Appendix B: Saltmarsh Habitat and Avian Research Program Nest Monitoring Protocols

Available online at www.tidalmarshbirds.org

NEST SEARCHING

Formal nest searches should be conducted as frequently as possible, but not so frequently as to cause detrimental disturbance to the birds. At a minimum, plots should be comprehensively searched at least once per week throughout the breeding season. When nest searching, the procedure is simply to walk back and forth in a zigzag fashion, with each path ~5-10 m from the previous one. Look carefully for behavioral cues, particularly birds that flush within 15 meters of you as you walk. Also watch for repeated flushes from the same spot, noticing when birds are carrying food (your impression will be of a decidedly "front-heavy" bird, because of the bits of prey sticking out of the bill) or fecal sacs (gleaming white). There is also an indescribable element involved with finding nests that just comes with experience. Your best bet is to go out with someone who has found some nests and look at where the nests are. Most people get quite good at finding nests quite quickly, though no one ever believes that they will. Finally, always pay attention for behavioral cues and opportunistically nest search at all times on the plot (e.g. while conducting nest checks, vegetation surveys).

MARKING NESTS

Once nests have been found, they should be marked with flags and the geographic coordinates taken directly over the nest recorded with a geographic positioning system device. A nest card should be filled out right away, and it is usually helpful to draw a small map of the immediate area on the back of the card, in order to help re-find the nest on subsequent visits (especially if it is not you who will be coming back). The types of thing worth marking on the map include the relative position within the plot, location of nearby ditches or pools, any boundaries between vegetation types (e.g., the border of a patch of *Juncus* sp.), etc.

We avoid putting flags right next to nests so as not to alert predators to the nest's location. Instead, use one of these methods; (a) place a flag ~5 m (5 strides) away, such that the nest lies on a line between the flag and some easily identified marker (e.g., an osprey platform or plot boundary marker), (b) if there is no suitable marker, put out two flags each ~5 m away from the nest, such that the nest lies directly between them, or (c) use a standard compass bearing to set the line between the flag and the nest. For any particular research group it is a good idea to make the convention consistent.

Nest numbering

To make it easier to combine data sets from different research groups, we will all use a common nest numbering system. Each nest should be given a number that consists of (1) the two letter study plot code, (2) the last two digits of the year, (3) the 4-letter banding code denoting the species, and (4) three numbers denoting the Nth nest found that year, so that numbers take the form: ZZYYXXXX###, where ZZ is the two-letter code for the study plot where the nest occurred, YY denotes the year, XXXX is the species code, and ### is the nest number.

Within each research group, all nests are numbered sequentially, without regard to species. For example, if the first three nests found in Connecticut in 2011 were a Saltmarsh Sparrow at Barn Island, a

Willet at Hammonasset, and another Saltmarsh Sparrow at East River, they would be numbered BI11SALS001, HM11WILL002, ER11SALS003.

If multiple field teams are working in the same area in the same year, or if people are working separately during nest searching, then each should be designated a separate set of numbers to use, so as to ensure that no number is used twice. For example, one person could take numbers starting from ZZYYXXX001, while another takes numbers starting from ZZYYXXX201.

Under-construction nests

For nests found without eggs, usually via a female flush during the construction phase, mark them as you would an active nest with a stake flag. Record the date found and the location using geographic coordinates for each nest found under construction on a new nest card.

To prevent disturbance that could lead a female to abandon her nesting attempt during the construction stage, do not revisit under-construction nest until at least 5 days after discovery when it might have eggs. In the meantime, stay away from the nest as much as possible; ideally leave an approximately 50m buffer, although the presence of other nests that need monitoring may influence the buffer radius). To this end, you might find it useful to mark the flag differently, such as with colored flagging that denotes “under construction” so the area can be avoided at a distance.

If an under-construction nest has eggs on a subsequent visit, assign it a unique number and open a new nest card for it if you haven’t already. If the nest never has eggs on subsequent visits, be sure you recorded the date of discovery and geographic coordinates, and then remove the flag after a few weeks.

NEST MONITORING

Nests should be visited every 3-4 days after finding to track nest contents. Three days is preferred for use in the fecundity model required by a SHARP deliverable. Nest visits should be brief and every attempt should be made to minimize disturbance. If you can see into the nest and count contents without getting right up close, then do so (carrying a narrow bamboo stick can be helpful as it allows you to part the vegetation without getting right up next to the nest). If nestlings are present, make note of physical features indicating their approximate age (feather development, body size, open eyes). If any eggs or nestlings are seen outside of the nest (especially after a flooding event), make note of that.

If any eggs or chicks are missing since your last visit, make a thorough search of the area around the nest to see if there are drowned chicks, or eggs that have floated out. If a nest appears to have flooded and has lost an egg or two, continue monitoring with nest checks at the normal intervals, because females will persist in incubation and the remaining eggs often hatch. If a nest with chicks appears to be empty, but it is too soon for them to fledge, also keep monitoring, because young chicks can climb out of nests and hide in the surrounding vegetation. Make sure to check where you put your feet.

Details of each visit should be recorded on the appropriate nest record card (see below). When nest contents have gone missing, it is important to provide as much detail as possible, both about what you do see and what you do not (e.g., broken egg shell, chewed body parts, any nest damage, nest empty but dry, etc.) Information about other nests lost in the same area and timeframe can be

especially helpful to record, although the fate of one nest should not be simply inferred from the fate of others. All of this information will be used to assign nest fates at a later date.

NEST CARDS

Whenever you go out in the field, carry a batch of blank nest cards so that you can fill in basic information when you first find a nest. When doing a series of nest checks, take the relevant nest cards with you so that you (a) have a map and directions to the nest, (b) know the conditions on the last visit, which can sometimes help explain what you find, and (c) can fill the information in directly to avoid transcription errors later on. Nest cards should be printed on fairly stiff card stock or Rite in the Rain paper so that they can withstand some abuse, but remember that these are primary data so take care not to get them wet, muddy, etc.

General nest info

Fill in the top section with the appropriate information about the nest and study plot when you first find the nest. Use the nest numbering system described above. Record the geographic coordinates of each nest using a geographic positioning system device. Record the band number of the associated female if she is trapped off of the nest. As noted previously, sketch a map of the nest location on the back of the nest card to assist finding the nest on subsequent nest checks.

Individual visit info

For each nest visit, the nest card has places where you should note:

- date and time of nest visit, observer initials
- the number of eggs and chicks in the nest,
- whether the nest bowl is wet (i.e. from flooding),
- whether eggs were warm or not (lightly touch them in the nest to check),
- the age of any chicks (estimated from the Nestling Aging SOP, available on SHARP website: www.tidalmarshbirds.org),
- whether any dead eggs or chicks were collected,
- whether a female was seen to flush as you approached the nest,
- how far you were from the nest when the female flushed,
- whether the female called (also known as ‘chipping’) at you as you approached the nest,
- how far you were from the nest (NOT the female) when mobbing began.

There is also a column for nest status on each visit (e.g., partially failed due to flooding, completely failed due to depredation). Codes for use in this column are in the margin on the right of the card.

Assigning codes is not always straightforward and a full assessment may not be possible until after the nest has completed. During the nest visits, however, simply assign the code that you think most accurately reflects the nests’ status for the period since the previous visit. Criteria for each status are described below.

In the “Notes” space below each visit’s row of boxes you can describe any changes in the nest’s integrity (e.g., pulled apart by a predator), whether the nest appears damp (e.g., due to flooding), whether and how many dead eggs/chicks were found, and any other information that may help assign a fate to the nest.

NEST FATE ASSIGNMENT

To minimize variation in how fates are assigned, nest fates should be completed by the graduate student responsible for each study plot (in consultation with others, as necessary). Described below are nest fate assignment rules, which should be followed closely to ensure consistency across individuals.

Ultimate nest fates relate to the factor that determined the “completion” of the nest, and is measured according to mutually exclusive categories. In other words it is the fate that relates to the last individual(s) in a nest.

- If any individual fledges, then the nest would be assigned an ultimate fate of “Fledged” (=“successful”).
- If no individual fledges, then the nest would be assigned an ultimate fate of “flooded”, “depredated”, or “failed, unknown cause” (all of which = “unsuccessful”).
- In cases of conflicting evidence, specifically both nest flooding and nest depredation evidence, nest fate is considered “completely failed, unknown cause”.
- If it is not certain whether any individuals fledge, then the nest would be assigned an ultimate fate of “unknown fate”.

Nest fate assignment requires tracking the nestling period of each nest that hatches to determine if missing chicks were old enough to fledge. Although eggs are laid a day apart, most species (including sparrows, shorebirds, ducks) will not start incubating until the clutch is complete. This means that the eggs will usually hatch on the same day. Our conventions are that the first day of the complete clutch is considered the first day (day 1) of incubation, and that the day on which eggs hatch is considered day 0 of the nestling phase (i.e., nestlings are considered 1 day old on the day after hatching occurs).

Incubation lasts approximately 12 days for Saltmarsh Sparrows, and the last day of incubation is also hatch day when the chicks are aged 0 days. Nestlings usually fledge after 10 days, when they are aged 9 days with our hatch day = 0 days old convention (Greenlaw & Rising, 1994). In summary, the entire brooding cycle proceeds as follows. Egg-laying: 1-5 days; incubation: approximately 12 days (last day is hatch day when chicks are 0 days old); nestling phase: typically 10 days, between 9 and 13 days.

NEST FATE ASSIGNMENT KEY

Below is a dichotomous key for nest fate classification. Apply these rules to the ultimate fate of the nest, as defined as the fate of the last egg or chick surviving within the nest. For example, though a nest may lose an egg to flooding during incubation but the remaining eggs hatch and the chicks fledge, the ultimate nest fate is

1 - At previous visit, chicks were 9+ days old (5)

1 - At previous visit, chicks were <9 days old (2)

2 - At current visit, chicks would be 9+ days old (8)*

2' - At current visit, chicks would be < 8 days old (13)*

2'' - At current visit, chicks would be 8 days old (17)*

5 - Spring tide or heavy rainfall occurred since previous visit (6)

5' - No spring tide or heavy rainfall occurred since previous visit (7)

6 - Evidence of flooding (**flooded**)

- the nest is observed underwater during a high tide and a subsequent nest check confirms that the nest is missing contents
- the nest is found with intact eggs outside the nest
- the nest is found with intact cold or dirty eggs in the nest, and eggs do not subsequently hatch
- the nest is found with intact dead chicks in, or close to, the nest
- the nest is found with barely-alive nestlings
- the nest is found to be empty and soaking wet immediately (next day) after a high tide, was known to have been active immediately prior to the high tide, and there are no signs of depredation (see 7 for criteria required to assign depredation)

6' - No evidence of flooding (7)

6'' - Evidence of flooding and depredation (**failed, unknown cause**)

7 - Evidence of depredation (**depredated**)

- the nest is found with its structure pulled apart
- the nest is found with obvious depredation remains

- dead chicks or eggs are found with injuries that likely resulted in death
- the nest is found empty, or with partial loss, on a day when the tides could not have accounted for the losses

7' - No evidence of depredation (**fledged**)

8 - No eggs/chicks missing, cold, or past hatch date (**active**)

8' - At least one egg/chick missing, cold, or past hatch date (9)

9 - Spring tide or heavy rainfall occurred since previous visit (10)

9' - No spring tide or heavy rainfall occurred since previous visit (11)

10 - Evidence of flooding (**flooded**)

- the nest is observed underwater during a high tide and a subsequent nest check confirms that the nest is missing contents
- the nest is found with intact eggs outside the nest
- the nest is found with intact cold or dirty eggs in the nest, and eggs do not subsequently hatch
- the nest is found with intact dead chicks in, or close to, the nest
- the nest is found with barely-alive nestlings
- the nest is found to be empty and soaking wet immediately (next day) after a high tide, was known to have been active immediately prior to the high tide, and there are no signs of depredation (see 7 for criteria required to assign depredation)

10' - No evidence of flooding (11)

10'' – Evidence of flooding and depredation (**failed, unknown cause**)

11 - Evidence of depredation (**depredated**)

- the nest is found with its structure pulled apart
- the nest is found with obvious depredation remains
- dead chicks or eggs are found with injuries that likely resulted in death
- the nest is found empty, or with partial loss, on a day when the tides could not have accounted for the losses

11' - No evidence of depredation (12)

12 - Nest intact, well worn, may have droppings in the nest or immediately adjacent (**fledged**)

12' - Conflicting evidence (**unknown if successful or failed**)

13 - No eggs/chicks missing, cold, or past hatch date (**active**)

13' - At least one egg/chick missing, cold, or past hatch date (14)

14 - Spring tide or heavy rainfall occurred since previous visit (15)

14' - No spring tide or heavy rainfall occurred since previous visit (16)

15 - Evidence of flooding (**flooded**)

- the nest is observed underwater during a high tide and a subsequent nest check confirms that the nest is missing contents
- the nest is found with intact eggs outside the nest
- the nest is found with intact cold or dirty eggs in the nest, and eggs do not subsequently hatch
- the nest is found with intact dead chicks in, or close to, the nest
- the nest is found with barely-alive nestlings
- the nest is found to be empty and soaking wet immediately (next day) after a high tide, was known to have been active immediately prior to the high tide, and there are no signs of depredation (see 7 for criteria required to assign depredation)

15' - No evidence of flooding (16)

15'' – Evidence of flooding and depredation (**failed, unknown cause**)

16 - Evidence of depredation (**depredated**)

- the nest is found with its structure pulled apart
- the nest is found with obvious depredation remains
- dead chicks or eggs are found with injuries that likely resulted in death
- the nest is found empty, or with partial loss, on a day when the tides could not have accounted for the losses

16' - No evidence of depredation (**failure, unknown cause**)

17 - No eggs/chicks missing, cold, or past hatch date (**active**)

17' - At least one egg/chick missing, cold, or past hatch date (18)

18 - Spring tide or heavy rainfall occurred since previous visit (19)

18' - No spring tide or heavy rainfall occurred since previous visit (20)

19 - Evidence of flooding (**flooded**)

- the nest is observed underwater during a high tide and a subsequent nest check confirms that the nest is missing contents
- the nest is found with intact eggs outside the nest
- the nest is found with intact cold or dirty eggs in the nest, and eggs do not subsequently hatch
- the nest is found with intact dead chicks in, or close to, the nest
- the nest is found with barely-alive nestlings
- the nest is found to be empty and soaking wet immediately (next day) after a high tide, was known to have been active immediately prior to the high tide, and there are no signs of depredation (see 7 for criteria required to assign depredation)

20' - No evidence of flooding (19)

20'' – Evidence of flooding and depredation (**failed, unknown cause**)

20 - Evidence of depredation (**depredated**)

- the nest is found with its structure pulled apart
- the nest is found with obvious depredation remains
- dead chicks or eggs are found with injuries that likely resulted in death
- the nest is found empty, or with partial loss, on a day when the tides could not have accounted for the losses

20' - No evidence of depredation (**unknown if successful or failed**)

NEST AND VISIT CENSORING

For nest survival analysis (e.g. logistic exposure), nest monitoring data must be censored to eliminate known biases. For example, if nestlings *could* have fledged on a given visit date (chicks were 9+ days old, in the case of Saltmarsh Sparrows) and their nest is found empty, the visit must be removed. In this case, the nest is assumed to be fledged while it may have failed after the previous visit with no evidence of failure left. By removing the final visit when the nestlings *could* have fledged, the potential positive bias is eliminated and all previous visits contribute to survival estimates. See Shaffer (2004) for discussion of this issue and an illustrative example.

Data that must be censored from nest monitoring before deriving survival estimates and the known problems they introduce:

- Nests that were found after failure – Even when evidence of cause of failure is available at the nest site, the timing of failure is not known and therefore the nest cannot be included.
- Nest visits when nestlings *could* have fledged, specifically nests with chicks that would be 9+ days old – See above. We also exclude nest visits when nestlings were 8 days old because previous research suggests that at 8 days (with hatch day = day 0), nestlings may fledge though it is rare (Greenlaw & Rising, 1994). To correct nest visits when chicks were 8 days old, remove the final nest visit and change the ultimate nest fate from “unknown if fledged or failed” to “fledged”, which allows the nest to contribute to daily survival probabilities without introducing bias.
- Nest visits when the nest was already inactive on the previous visit – Note that, in the field it is best to be conservative (continue to visit a nest until you are sure it has failed); however, this practice results in nests that were visited more than once after failure. Left unchanged, these additional visits can result in erroneous assigned times of failure and exposure intervals.
- Nest visits that are 6 or more days after the previous visit - We restrict our analyses to nests visited more frequently to limit uncertainty in nest fate assignment and the timing of nest completion.

Appendix C: Decision Support Tools – Delaware case study



Incorporating climate change with conservation planning: a case study for tidal marsh bird conservation in Delaware, USA

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ABSTRACT: Northeastern USA tidal marshes provide critical ecological services, including carbon sequestration, water filtration, storm protection, erosion control, and wildlife habitat. Regardless of the services provided, salt marshes have been filled, drained, and degraded since European settlement, and the unique wildlife dependent on these ecosystems requires immediate conservation action. Furthermore, global sea level rise has become the foremost cause of contemporary and future marsh loss. Sea levels have risen approximately 2 mm/year over the last century and predicted marsh losses due to sea level rise are estimated to be 0.5–1.5% annually. Increases in marsh flooding from sea level rise creates a real and immediate challenge to tidal marsh bird persistence, and uncertainties surrounding sea level rise must be integrated into conservation decisions to achieve smart and proactive conservation planning. Decisions about how to allocate limited conservation funding are often subjective and lack quantitative and repeatable methodologies. To assist with prioritizing salt marsh habitat protection, we tested two quantitative methods (benefit targeting and binary linear programming optimization) to determine the best combination of unprotected tidal marsh parcels that would yield the greatest conservation benefit. We used three budget level scenarios (\$10M, \$15M, and \$20M) to develop budget specific parcel portfolios based on benefit targeting and optimization, and used tidal marsh obligate breeding bird density as our conservation target. We used three sea level rise scenarios (0.5 m, 1.0 m, and 1.5 m) to estimate the land cover types that would remain within each selected parcel following a rise in sea level. The optimization method selected more

abstract continued

parcels, protected more marsh area, and conserved more tidal marsh obligate birds than the more traditional benefit targeting method. Total marsh area ranged from 7.2–9.6% greater and bird density ranged from 7.3–12.8% greater given the optimization method. When benefit targeting and optimization protected the same number of birds, optimization provided a cost savings of \$1.75M–\$2.9M. All sea level rise scenarios inundated greater than 95% of the wetland area on selected parcels. Agricultural land had the greatest amount of area remaining of any land cover type in all scenarios, ranging from 79.9 ha, 82.0% of total portfolio area (\$10M–1.5 m scenario), to 648.7 ha, 70.8% of total portfolio area (\$20M–0.5 m scenario). Optimization models can be used to develop comprehensive strategies that protect marshes with current core tidal marsh bird populations. However, increasing rates of inundation from sea level rise will likely lead to losses of existing wetland areas. The potential future benefits of adjacent agricultural lands to tidal marsh birds through marsh migration should be incorporated into optimization models for more effective conservation planning and spending of limited financial resources.

Keywords: *benefit targeting, binary linear programming, bird density, conservation planning, marsh birds, conservation optimization, sea level rise, tidal marsh*

INTRODUCTION

Tidal marsh ecosystems provide essential ecological services including; protecting shorelines from erosion and strong wave dynamics, serving as areas for flood storage, acting as nursery habitat for marine organisms, and improving water quality (Greenburg 2006). Despite these critical functions, few marshes remain in pristine condition and the majority of marshes have historically experienced severe alterations. Development (Takekawa et al. 2006), agriculture (Dreyer and Niering 1995), ditching and channelization (Daiber 1986), marsh burning (Nyman and Chabreck 1995), invasive species (Benoit and Askins 1999), pollutants (Bertness 1999), and global climate change (Arp et al. 1993), have contributed to extensive marsh loss and degradation of remaining areas (Tiner 1984, Dahl 1990).

Of the 25 vertebrate species restricted to salt marsh habitats, 21 species or recognized subspecies are considered endangered, threatened, or of other heightened conservation concern in the United States (Greenburg 2006). Tidal marsh birds are of particular concern, as population estimates or trends are unknown and much of the habitat may be inundated in the near future. Several avian species spend their entire annual life cycle in tidal marshes and nest near or directly on the marsh surface (e.g., Clapper rail [*Rallus longirostris*], Willet [*Tringa semipalmata*], Saltmarsh sparrow [*Ammodramus caudacutus*], and Seaside sparrow

[*A. maritimus*]), therefore their reproduction is directly tied to flooding events (Gjerdrum et al. 2005, 2008, Shriver et al. 2007). Increases in flooding from sea level rise pose real immediate challenges to the persistence of tidal marsh bird populations as 0.5–1.5% of global marshes are predicted to be lost annually due to inundation (Shriver and Gibbs 2004, Greenburg 2006, Dahl and Stedman 2013).

Conservation of salt marsh habitat is a high conservation priority, particularly in light of accelerated sea level rise (Douglas 1991, IPCC 2007, Rahmstorf 2007). Furthermore, the U.S. has a greater opportunity for tidal marsh conservation than other nations, given one-third of the global extent (4,500,000 ha) of tidal marshes are located along the country's Atlantic and Gulf coasts (Greenburg 2006). To prepare for the challenges tidal marshes face from global climate change, conservation decisions must be made using objective, quantitative and repeatable methods that incorporate sea level rise uncertainties. Such decision-making should effectively prioritize land acquisitions and efficiently allocate limited conservation funds while proactively addressing potential future habitat changes.

Two selection methods used by conservation planners to identify priority projects for land acquisition or easement opportunity vary in their capacity to select cost-effective projects given the fiscal constraints of limited budgets. Benefit targeting is a rank-based method that uses a

“greedy agent” algorithm to acquire parcels with the highest conservation value, independent of project costs, until a specified budget is exhausted. These “greedy heuristic algorithms” are routinely used in conservation planning for reserve site selection (Margules et al. 1988, Pressey and Nicholls 1989, Bedward et al. 1992, Freitag et al. 1997, Cabeza and Moilanen 2003) and, given the availability of avian data, these taxa are well represented as a measure of the conservation benefit in reserve selection projects (Sætersdal et al. 1993, Fairbanks et al. 2001). Although benefit targeting continues to be the most used method for developing conservation planning strategies, the method’s outcomes can lead to inefficient monetary spending and suboptimal conservation gains (Underhill 1994, Rodrigues and Gaston 2002, Messer 2006, Messer and Allen 2010, Duke et al. 2013). Alternative methods to benefit targeting include linear, binary, and mixed integer programming. These optimization algorithms find solutions that minimize the expenditure of financial resources while simultaneously maximizing a desired conservation target (Allen et al. 2011, Kaiser and Messer 2011). Optimization algorithms are being used more frequently to answer a variety of conservation questions (Williams and ReVelle 1998, Haight et al. 2004, Crossman and Bryan 2006, Martin et al. 2007, Downs et al. 2008, Stralberg et al. 2009, Fooks and Messer 2012, Fooks and Messer 2013).

Herein, we present a case study that compares the site prioritization between benefit targeting and optimization and then determines the future persistence of the selected parcels given three sea level rise scenarios and the implications for the tidal marsh bird community. Our specific objectives were to: 1) determine the tidal marsh areas in Delaware that support the greatest density of breeding tidal marsh obligate birds, 2) identify the extent of protected and unprotected salt marsh habitat in the state, 3) identify and compare benefit targeting- and optimization-selected parcel portfolios that maximize bird density on unprotected marsh habitat in three budget scenarios, and 4) determine the effect of three sea level rise scenarios on the proportion of land cover types within the optimized parcels.

METHODS

Parcels with Unprotected Marsh

To determine the extent of unprotected marsh in Delaware’s Kent and Sussex counties, we assessed publicly available geographic information systems (GIS) data from the Protected Areas Database (PAD) and the National Conservation Easement Database (NCED) (Data Basin - Conservation Biology Institute 2012). The PAD-US 1.1 - Conservation Biology Institute Edition (CBI Edition) is currently the most comprehensive geospatial dataset of U.S. protected areas. The NCED compiles conservation easement information from land trusts and public agencies and is the first such national database.

We used ArcMap10 (ESRI 2011) to overlay PAD-US 1.1 (CBI Edition) and NCED (Version 1, 2011) data on U.S. Fish & Wildlife Service (USFWS) National Wetlands Inventory (NWI) estuarine emergent marsh spatial data (USFWS 2012). We evaluated the extent of marsh habitat currently protected through ownership or conservation easements and used a series of geoprocessing tools to identify and extract marsh areas currently unprotected. We obtained geospatial land parcel data for Kent and Sussex counties from the Delaware DataMIL (Delaware Geological Survey 2012) and overlaid the data on the unprotected marsh spatial information. We identified the parcels that contained unprotected marsh and calculated marsh area for each parcel.

Parcel Conservation Easement Costs

We calculated easement costs of parcels with unprotected marsh using values from an existing hedonic analysis, originally developed to estimate agricultural easement values (Allen et al. 2006). Allen et al. (2006) calculated regression coefficients from 501 parcels previously acquired by the state of Delaware for agricultural lands conservation to estimate easement costs of 1,095 unprotected parcels not formally appraised in Kent County (2006). We included the following variables relevant to calculating marsh conservation easement costs in our linear cost equation: county, tillable ha, tillable ha², forest ha, forest ha², wetland ha, wetland ha², year 2001, distance to shore (km), and distance to urban area (km) (Table 1). The county variable

accounted for each easement's initial base price and an additional \$100,661 was added to easement costs to control for market inflation relative to 1995, the baseline year analyzed in the hedonic analysis (Allen et al. 2006).

We estimated land cover for each parcel in ArcMap 10 (ESRI 2011) using 2007 Delaware land use/land cover (LU/LC) geospatial data (Delaware Geological Survey 2012). We defined our land cover classes as tillable areas, forested areas (including deciduous, evergreen, and mixed forest), and wetland areas (including all non-tidal and tidal wetland classes). We used the Delaware state boundary line to calculate distance to shore and the boundaries of incorporated municipalities to calculate distance to urban area (Delaware Geological Survey 2012). We multiplied parcel variable values by their associated monetary value listed (Table 1), and summed or subtracted where appropriate to obtain an estimated parcel easement cost.

Bird Surveys

We conducted this study in tidal salt marsh habitat in Kent and Sussex counties, Delaware. These marshes are classified as Northern Atlantic Coastal Plain Tidal Salt Marsh and range from the southern coast of Maine to the Chesapeake Bay, Virginia (Comer et al. 2003). This system of salt marshes occurs on the bayside of barrier beaches and along the outer mouth of tidal rivers where salinity has not been strongly impacted by freshwater.

We used a two-stage cluster sampling design to randomly distribute survey points within the Saltmarsh Habitat & Avian Research Program (SHARP, www.tidalmarshbirds.org) study area (Johnson et al. 2009), which extends through Bird Conservation Region (BCR) 30 and north to Lubec, Maine. BCR 30, also known as the New England/ Mid-Atlantic Coast BCR, is a bird conservation planning

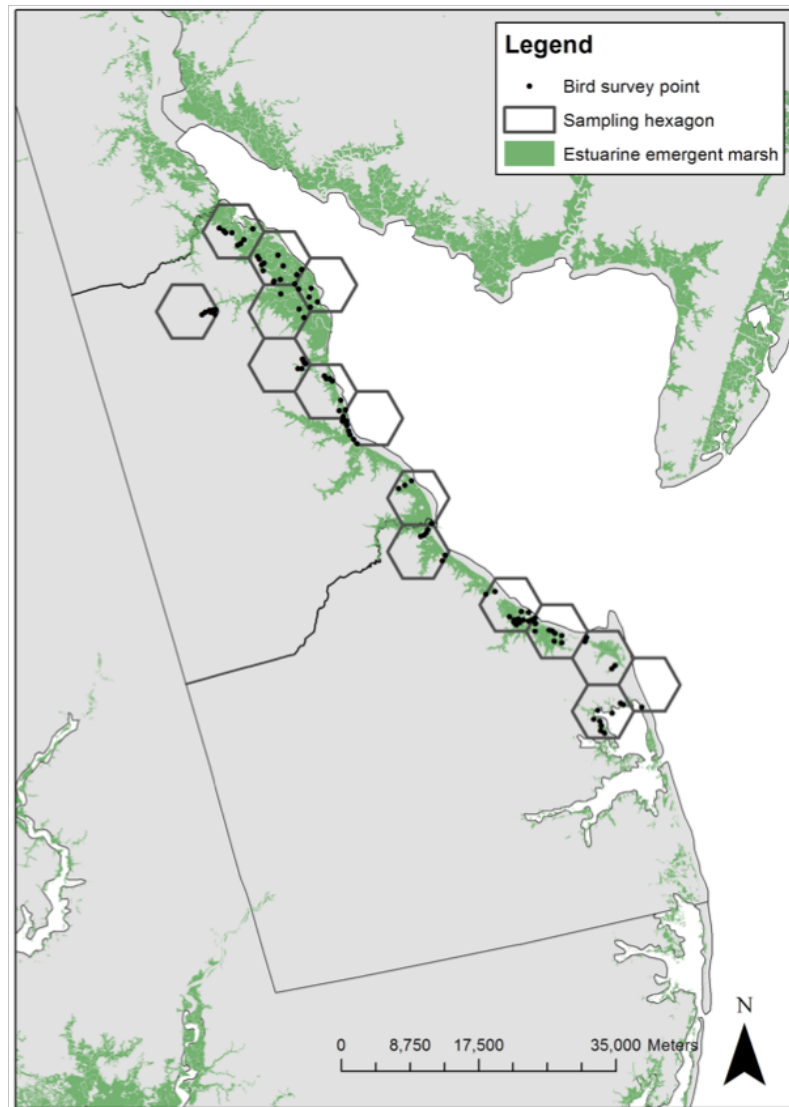
Table 1: Hedonic analysis variables and associated values and interpretation used to calculate marsh conservation easement costs. *Modified from Allen et al. 2006.*

Variable	Value	Interpretation
County	+ \$157,629.09 (Kent) + \$193,107.05 (Sussex)	County location constant
Tillable ha	+ \$ 7,289.02	Increase per tillable hectare
Tillable ha ²	- \$ 13.37	Value increases at a decreasing rate when the number of tillable hectares increases
Forest ha	+ \$ 9,111.42	Increase per forest hectare
Forest ha ²	- \$ 59.90	Value increases at a decreasing rate when the number of forest hectares increases
Wetland ha	+ \$ 3,644.46	Increase per wetland hectare
Wetland ha ²	- \$ 17.77	Value increases at a decreasing rate when the number of wetland hectares increases
2001	+ \$100,660.62	Inflation (relative to 1995)
Distance to shore (km)	- \$ 4.77	Decrease for each kilometer away from the shore
Distance to urban area (km)	- \$ 15.71	Decrease for each kilometer away from the nearest urban area

region administered by the Atlantic Coast Joint Venture that extends from coastal Virginia through southern coastal Maine (Steinkamp 2008). The primary sampling units (PSUs) selected during the first-stage were 40km² hexagons used by the National Marsh Bird Monitoring Program (Seamans 2011), (Figure 1). During the second-stage of site selection, we used NWI estuarine emergent marsh geospatial data to randomly distribute the survey points (secondary sampling units [SSUs]) across marsh habitat within selected PSUs (USFWS 2012).

We used a generalized random tessellation stratified (GRTS) survey design in Program R using the spsurvey package to generate survey points (Kincaid and Olsen 2012, R Core Team 2010). Samples from GRTS survey designs emphasize spatial-balance, exhibiting spatial density patterns that closely mimic the spatial density patterns of the resource. We randomly located up to 10 survey points in each hexagon within estuarine emergent marsh. Points were at least 400 m apart to ensure independence (Conway 2011).

Figure 1: Bird sampling locations for this study in Kent and Sussex counties, Delaware, USA. Hexagons are the primary sampling units, n = 15, and bird survey points are the secondary sampling units, n = 102.



Trained field technicians collected bird survey data during the 2011 avian breeding season (May–July) at 102 survey points in Delaware for SHARP. At each survey point, field technicians conducted point-count surveys following the Standardized North American Marsh Bird Monitoring Protocol (Conway 2011). We conducted bird surveys from 30 minutes prior to sunrise and completed surveys before 11:00 a.m. We visited each survey location three times during the breeding season and we did not survey for breeding birds when wind speed was greater than 12 mph or during sustained rain or heavy fog. Each survey consisted of a five-minute passive listening period during which we recorded all individual birds seen or heard utilizing the marsh in one of three distance categories: 0–50 m, 50–100 m, 100+ m. We did not record species flying over the survey area or not actively foraging within the marsh.

Conservation Benefits

We used SHARP's Delaware bird survey data to calculate Clapper rail, Willet, Saltmarsh and Seaside sparrow densities based on point-count detections from the 0-50 m and 50-100 m distance categories. We estimated bird density (birds/ha) as the total number of individuals detected for the four species combined. We used the survey data to determine the maximum number of individuals detected across the three surveys at each survey point. We summed the maximum count values within a hexagon and divided by total survey area to calculate bird density (birds/ha) within each hexagon. Total survey area was calculated by multiplying the area of the point-count circle (radius = 100m) by the number of points surveyed within the hexagon. We used the mean bird density for surveyed hexagons to estimate bird density in unsurveyed hexagons. To calculate the parcel-specific bird density for estuarine emergent marsh, our "conservation benefit," we multiplied the bird density estimate by the area of unprotected marsh within the parcel.

Parcel Selection

We used benefit targeting and binary linear programming optimization and compared the selected parcels between the two methods to determine which method provided the greatest conservation benefit. The benefit targeting method typically selects parcels to acquire based on benefit values and does not take into account easement or transaction

costs explicitly in the selection process. Parcels are listed in descending order of benefit value; the parcel with the highest benefit score is acquired first, and the process continues until the budget is exhausted. Binary linear programming optimization evaluates the conservation benefits of the entire parcel pool, as well as estimated costs and budget constraints, to select a combination of parcels that provides the greatest aggregate conservation benefit within the constraints (Messer 2006). Optimization selects parcels that contribute to achieving the maximum total benefit possible within the apportioned budget. Model output is restricted to the integers 0 and 1, where a value of 0 indicated parcel rejection for land acquisition and a value of 1 indicated parcel selection. The resulting binary portfolio represents the best use of conservation dollars to conserve important core areas of four of Delaware's tidal marsh obligate bird species. The optimization model was expressed as,

$$\max(X) = \sum_{i=1}^I X_i A_i$$

The model was represented by $i = 1, \dots, 1,447$, which indicated an index representing the 1,447 land parcels available for purchase. Conservation benefit (parcel bird density) was represented as A_i , and X_i represented the binary (0, 1) variable for the i th parcel. The model was subject to a budget constraint, where C_i was the cost of the i th parcel, and B was the total available budget,

$$\sum_{i=1}^I C_i X_i \leq B$$

We used Analytic Solver Platform and Microsoft Excel to perform benefit targeting and optimization analyses (Frontline Systems 2013).

We used three budget scenarios (\$10M, \$15M, and \$20M) for each selection procedure and allocated the entire budget within each scenario to tidal marsh conservation. The base budget level (\$10M) represented the State of Delaware's 2013 Open Space Preservation budget (State of Delaware - Office of the Governor 2012). The \$15M and \$20M scenarios were analyzed in addition to the base level to evaluate the relationship between selection methods with an increased budget. The greater budgets could also be used for multi-year portfolios. We included a transaction fee of \$15,000 per parcel, as well as removed parcels less than 0.40 ha (1 acre) in total area to facilitate model computability.

Sea Level Rise Scenarios

To estimate the impact of different sea level rise scenarios on the land cover of the optimization-selected parcels, we grouped 2007 Delaware LU/LC classes into general categories and used ArcMap 10 to calculate changes in land cover area due to permanent inundation (Table 2; ESRI 2011, Delaware Geological Survey 2012). We calculated

land cover area within each optimal parcel under four sea level scenarios; current mean higher high water (MHHW), 0.5 m, 1.0 m, and 1.5 m above MHHW between current (2011) and 2100 (Delaware DNREC 2012). We used spatial polygons delineated from overlays by the Delaware Department of Natural Resources and Environmental Control to depict each sea level rise scenario (Delaware DNREC 2012).

Table 2: General land cover categories used to evaluate the impacts of sea level rise on optimization-selected parcels. Categories were comprised of 2007 Delaware Land Use/Land Cover (LU/LC) classes (Delaware Geological Survey 2012).

General land cover	2007 Delaware LU/LC class
Wetland	non-tidal emergent wetland
	non-tidal scrub/shrub wetland
	tidal emergent wetland
	tidal scrub/shrub wetland
Forested wetland	non-tidal forested wetland
Agricultural land	cropland
	mixed rangeland
	pasture
	shrub/brush rangeland
Forested upland	deciduous forest
	evergreen forest
	mixed forest
Developed/barren land	beaches and river banks
	farmsteads and farm related buildings
	mobile home parks/courts
	multi family dwellings
	other urban or built-up land
	recreational
	retail sales/wholesale/professional services
	single family dwellings
	tidal shoreline
	transitional (incl. cleared, filled, and gravel)
Water feature*	utilities
	bays and coves
	man-made reservoirs and impoundments
	natural lakes and ponds
	non-tidal open water
	tidal open water
	waterways/streams/canals

**Water features were present on optimal parcels, however, this general land cover was excluded from the sea level rise impact analysis since water features are already comprised of water.*

RESULTS

Parcels with Unprotected Marsh

We estimated the presence of 31,543 ha of salt marsh in Delaware with 22,148 ha protected and 9,395 ha unprotected. Unprotected marsh in Kent and Sussex counties totaled 6,129 ha of which there were 2,587 ha located on 947 parcels in Kent County and 3,542 ha located on 2,318 parcels in Sussex County (parcel total $n = 3,265$). We removed 1,818 parcels, each less than 0.40 ha in total area, from the parcel selection pool. Removed parcels contained 98 ha of total marsh (1.59% of the state's unprotected marsh habitat). In total, 1,447 parcels, 384 and 1,063 from Kent and Sussex counties respectively, were analyzed for parcel portfolio selection. The parcels contained 6,030 ha of unprotected marsh, ranging from 0 – 208.60 ha per parcel. Mean marsh area was 4.17 ha/parcel and median marsh area was 0.70 ha/parcel.

Parcel Conservation Easement Costs

Easements in Sussex County were \$35,478 greater than those in Kent County before landscape variable costs were

considered. The greatest increases in parcel easement cost due to the land cover variables were \$885,311 for tillable area (182.69 ha), \$264,498 for forest area (113.05 ha), and \$24,831 for wetland area (198.05 ha). Price increases reflect the difference between the whole area variable rate (e.g., tillable ha) and the area² variable rate (e.g., tillable ha²). Maximum cost values deducted for the distance variables were \$59 (12.38 km from shore) and \$153 (9.73 km from an urban area). Total easement cost for parcels in the selection pool ranged from \$258,193–\$1,387,190, with a mean cost of \$344,324 and a median cost of \$298,381.

Conservation Benefit

Tidal marsh obligate bird totals within the surveyed hexagons ranged from 0–126 individuals (Table 3). Bird density on surveyed hexagons ranged from 0.0–3.71 birds/ha (mean = 1.79 birds/ha, SE = 0.31). Bird density within parcels with unprotected marsh ranged from 0.0–643.53 birds/parcel (mean = 8.83 birds/parcel, SE = 0.81).

Table 3: Summary bird survey data by hexagon collected at 102 survey points in Kent and Sussex counties, Delaware, from May–July 2011.

Hexagon ID	Survey points	Survey area (ha)	Total birds	Mean birds/pt	Bird density (birds/ha)
68731	13	40.84	126	9.69	3.09
69123	7	21.99	0	0.00	0.00
69124	3	9.43	31	10.33	3.29
69517	5	15.71	13	2.60	0.83
69911	8	25.13	31	3.88	1.23
71485	9	28.28	105	11.67	3.71
71879	1	3.14	5	5.00	1.59
237327	8	25.13	24	3.00	0.95
237721	5	15.71	52	10.40	3.31
238507	7	21.99	9	1.29	0.41
239294	4	12.57	21	5.25	1.67
239687	6	18.85	58	9.67	3.08
240081	13	40.84	76	5.85	1.86
240475	4	12.57	9	2.25	0.72
240868	9	28.28	33	3.67	1.17

Parcel Selection

At the \$10M budget level, benefit targeting selected 13 parcels to maximize bird density for a total portfolio cost of \$9,912,597. Parcels contained 1,068 total ha of marsh and 3,150 birds. Binary optimization selected 18 parcels for a total cost of \$9,972,390, a 0.6% change from the benefit targeting portfolio cost. The optimization portfolio contained 77 more marsh ha and 319 more tidal marsh obligate birds than the benefit targeting portfolio, representing increases of 7.2% and 10.1% in conserved habitat and bird density, respectively (Figure 2).

With the \$10M budget level, the five parcels with the greatest bird densities were selected by both methods (Figure 3; Table 4). Benefit targeting selected three unique parcels including the most expensive parcel (\$1,387,190) and binary optimization selected eight unique parcels (Table 4). For benefit targeting to reach the 3,469 bird-conservation benefit secured by the optimization portfolio, an additional \$2,888,894 was required to purchase 3 more top-ranked bird density parcels. For a final cost of \$12.9M, purchasing the top-ranked 16 parcels would conserve 3,513 birds on 1,208 marsh ha, exceeding the \$10M optimized portfolio by 44 birds and 63 marsh ha.

When we increased the budget to \$15M, the optimization portfolio conserved 4,343 birds on 1,501 marsh ha, an

increase of 12.8% and 9.6% in birds and marsh area, respectively, from the benefit targeting portfolio (Figure 2). Twenty-nine parcels secured the larger total conservation benefit in the optimization portfolio at an additional cost of \$118,279; 0.8% over the total cost of the 19 parcels in the benefit targeting portfolio (\$14,866,046). Of the six parcels selected by benefit targeting but not by optimization, three had easement costs over \$1M and all six cost over \$750,000 (Table 4). An additional \$2.7M would be needed for benefit targeting to match the 4,343 birds conserved by optimization.

At the \$20M budget level, optimization selected 7 more parcels and the portfolio cost an additional \$28,107 (\$19,973,643 total) compared to the 28 parcels chosen with benefit targeting (0.1% change). The additional conservation benefit garnered by the optimal parcel combination equated to 344 birds and 163 marsh ha, increases of 7.3% and 9.6%, respectively, over benefit targeting benefits. The five parcels unique to the benefit targeting portfolio supported bird densities ranging from 90.54–119.84 birds/parcel, while the 12 parcels unique to the optimization portfolio supported bird densities from 53.73–89.69 birds/parcel (Table 4). At an additional cost of \$1.75M, benefit targeting would match the ~5,100 birds conserved by the optimized portfolio.

Figure 2: Percent change (increase) for three portfolio variables from the benefit targeting method to the optimization method, by budget scenario.

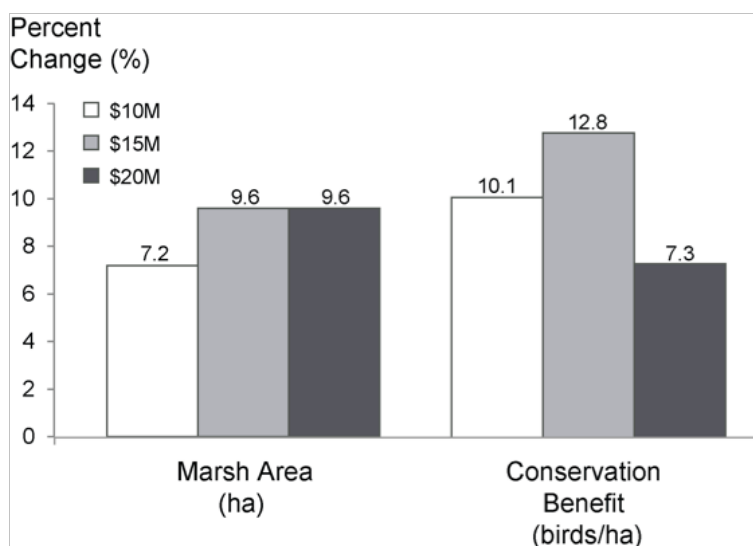


Figure 3: Conservation benefit (bird density) by parcel easement value for parcels selected in the \$10M budget scenario. Bubbles are shade-coded by selection method (benefit targeting [BT], optimization [OPT]) and bubble size represents parcel unprotected marsh area.

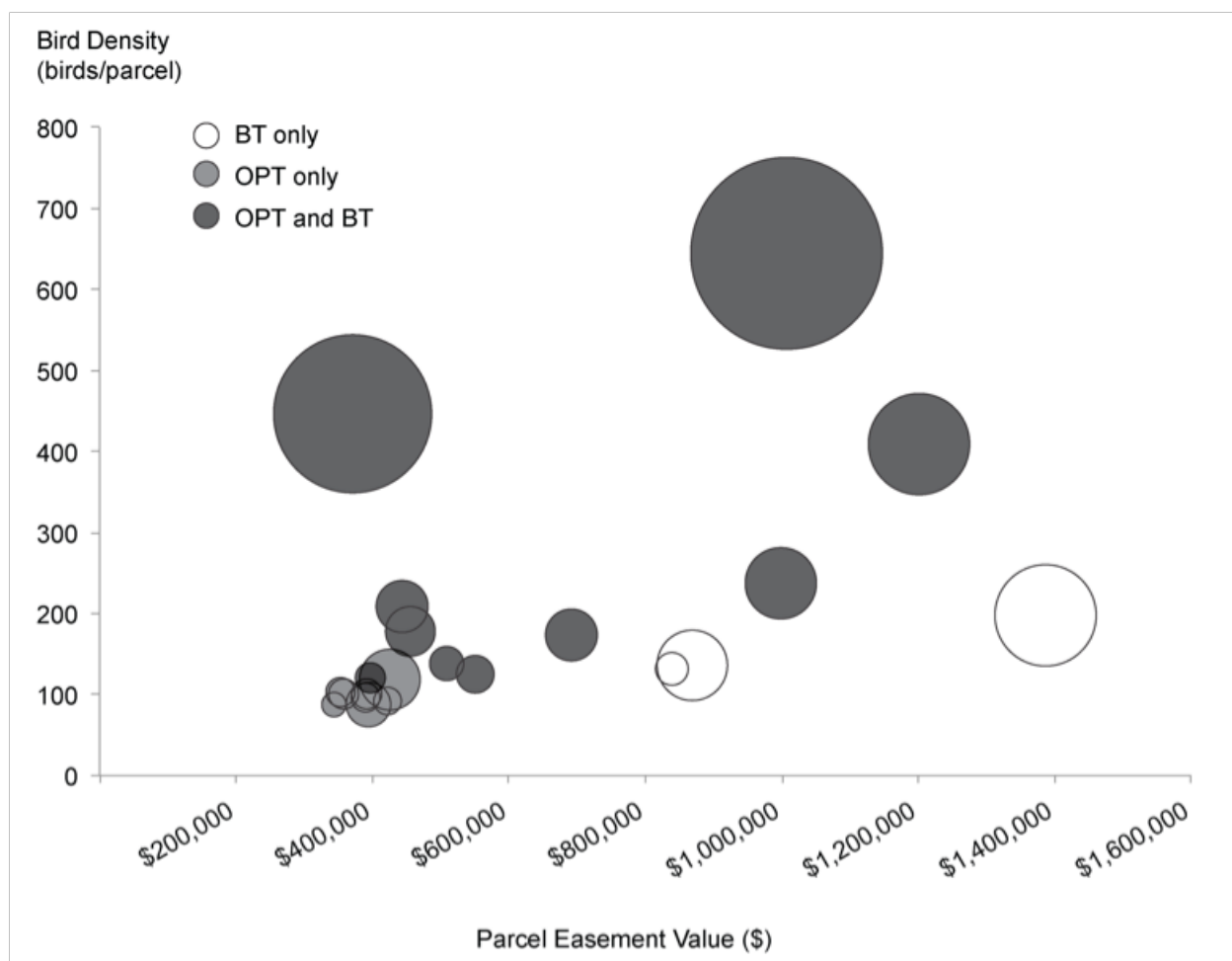


Table 4: Parcel portfolios selected by two parcel selection methods, benefit targeting (BT) and binary linear programming optimization (OPT), for three budget scenarios (\$10M, \$15M, \$20M). A table of parcel landscape variables, conservation benefits, and easement costs is presented. Marsh area refers to unprotected marsh.

BT	OPT	County/parcel ID (K [Kent]/ S [Sussex])	Total area (ha)	Marsh area (ha)	Bird density	Tillable area (ha)	Forest area (ha)	Wetland area (ha)	Dist to shore (km)	Dist to urban area (km)	Easement cost (\$)	Total cost (incl. trans fee; \$)
X	X	K/1-00-01300-01-0300-00001_3304	321.31	208.60	643.53	73.36	38.17	198.05	0.00	7.19	1,006,293	1,021,293
X	X	K/1-00-01300-01-0200-00001_3305	179.64	171.94	447.08	0.00	0.00	167.58	1.71	4.84	369,961	384,961
X	X	S/33500700000100_1146	251.88	110.20	409.24	92.22	22.72	130.57	1.48	0.00	1,201,231	1,216,231
X	X	S/33000400001700_93265	160.94	77.49	238.44	68.70	10.53	81.49	1.53	1.14	999,691	1,014,691
X	X	S/23501000000300_190798	57.39	56.49	209.79	0.00	0.00	56.66	1.19	1.19	443,195	458,195
X	X (20)	K/8-00-11400-01-0100-00001_75785	329.78	110.20	197.66	182.69	7.75	126.60	0.02	0.21	1,387,190	1,402,190
X	X	K/4-00-04900-01-0300-00001_37404	62.78	54.05	177.78	7.54	0.00	53.27	3.49	3.62	456,159	471,159
X	X	S/33000400000600_93358	127.99	56.43	173.64	28.83	4.37	63.86	3.30	2.82	691,686	706,686
X	X	S/23502300000300_190792	54.73	37.09	137.71	7.01	4.48	43.08	2.12	1.13	507,787	522,787
X	X (20)	S/33000300000500_93260	178.70	76.49	137.21	33.80	20.56	84.59	5.07	2.51	867,943	882,943
X	X (15/20)	S/23502300000202_189974	124.11	35.44	131.61	53.76	3.88	61.82	1.98	1.54	838,828	853,828
X	X	S/33001200001403_93322	74.86	40.86	125.73	16.83	2.46	39.06	3.09	0.61	549,912	564,912
X	X	S/23501700001500_189973	34.03	32.61	121.09	0.00	0.30	33.14	1.59	1.37	397,723	412,723
X (15/20)	X	K/7-00-10500-01-0200-00001_63336	85.44	65.95	118.29	0.00	0.46	65.98	5.21	1.29	425,551	440,551
X (20)	X	K/1-00-04000-01-0100-00001_3613	31.64	31.64	104.08	0.00	0.00	30.72	5.60	2.35	353,428	368,428
X (20)	X	S/33000500000100_93264	33.27	32.65	100.48	0.00	0.00	32.04	0.87	0.74	392,284	407,284
X (20)	X	K/5-00-16500-01-0200-00001_40362	32.72	32.61	100.34	0.00	0.00	32.51	2.53	2.16	357,958	372,958
X (20)	X	S/33000400001600_91672	31.55	31.37	96.52	0.00	0.00	31.11	2.53	2.12	389,899	404,899
X (20)	X	S/33000900000100_93317	35.18	29.87	91.91	5.05	0.00	29.96	1.26	0.74	423,480	438,480
	X	K/1-00-04100-01-0100-00001_	27.32	26.47	87.06	0.00	0.00	26.57	2.35	5.89	342,483	357,483
	X	K/5-00-12400-01-0401-00001_44363	49.08	48.38	86.79	0.03	0.06	48.30	0.29	2.12	393,671	408,671
X	X	K/5-00-12400-01-0301-00001_44355	109.66	68.42	122.74	28.08	3.74	73.19	0.00	0.90	657,222	672,222
X		S/33001200001400_93321	148.40	38.95	119.84	69.84	16.91	60.81	4.41	0.02	1,030,453	1,045,453
X		S/33400100000900_4688	161.63	32.26	119.78	70.08	47.97	40.34	3.09	0.61	1,156,219	1,171,219
X	X (20)	S/33000400001600_93266	88.83	36.32	111.75	41.54	7.29	39.26	2.53	2.12	752,413	767,413
X		S/23501600003600_189969	137.62	59.10	106.00	47.92	7.30	68.26	2.17	2.59	841,591	856,591
	X	K/4-00-03900-01-2600-00001_37211	26.18	26.18	86.13	0.00	0.00	25.52	6.16	1.77	339,681	354,681
	X	S/23402500002700_110688	70.69	43.84	78.63	0.00	0.00	35.95	0.00	5.87	401,723	416,723
	X	K/8-00-11300-02-1600-00001_75718	43.15	41.86	75.08	0.00	0.59	42.40	2.12	2.20	386,226	401,226
	X	S/33402500000200_1013	49.21	41.23	73.97	0.00	0.00	40.78	0.00	4.47	412,765	427,765
	X	S/33000500000101_92853	23.25	22.96	70.65	0.00	0.00	23.17	0.87	0.74	368,656	383,656
	X	S/23000300000900_93325	21.44	21.25	65.40	0.00	0.00	20.95	0.16	0.00	362,316	377,316
	X	S/33000500000600_93145	21.29	20.05	61.69	0.00	0.00	21.29	0.71	0.27	363,285	378,285
	X	S/33000500000401_93147	21.59	17.55	54.00	0.01	0.06	21.50	0.50	0.00	364,534	379,534
	X	S/23000100000100_93308	17.48	17.46	53.73	0.00	0.00	17.37	1.13	0.43	351,700	366,700
X		S/23000300000900_93328	104.65	33.59	103.36	48.69	7.96	47.57	0.82	0.00	818,872	833,872
X	X	S/13400800004200_55132	163.27	55.35	99.28	0.00	37.24	68.61	0.00	1.17	716,419	731,419
X		K/1-00-00300-01-1400-00001_2261	144.65	50.48	90.54	86.96	0.00	52.30	4.88	2.67	932,947	947,947
	X	S/33000400000700_93259	127.97	50.00	89.69	23.24	1.02	57.65	3.30	2.82	616,151	631,151
X	X	S/330005000002400_93271	55.55	28.93	89.02	25.14	0.09	28.65	0.74	0.18	559,202	574,202

Sea Level Rise Scenarios

Wetlands occupied approximately 50% of the portfolio area at current MHHW for the \$10M and \$15M portfolios, 397.47 ha and 495.93 ha, respectively, and 37% for the \$20M portfolio (627.67 ha; Figure 4). For all budget levels, over 95% of the initial wetland area was inundated with a 0.5 m rise in sea level and 100% was inundated with a 1.0 and 1.5 m rise (Table 5). The largest amount of wetland area remaining following inundation was 30.68 ha in the \$20M–0.5 m scenario, equal to 3.4% of the portfolio's total area (Figure 4).

Agricultural land accounted for 37–45% (395.23–772.84 ha) of the initial portfolio area(s) at current MHHW (Figure 4). The proportion of agricultural lands increased with increasing magnitude of sea level rise and occupied the largest area relative to the other land cover types at all levels of inundation. Agricultural lands occupied the largest portfolio area proportion, 84.4% (123.99 ha), in the 1.5 m

scenario at the \$15M budget level. Agricultural area losses due to inundation ranged from 74.98 ha (0.5 m scenario), or 23.9% of the original 313.36 ha of agricultural lands in the \$10M portfolio, to 398.76 ha (1.5 m scenario), 51.6% of the original 772.84 ha in the \$20M portfolio (Figure 4).

In general, forested upland and developed/barren land together comprised 20% or less of the area of the optimized portfolios. The largest amount of forested upland plus developed/barren land area was 244.76 ha at current MHHW (\$20M), and the smallest area was 17.24 ha at 1.5 m (\$10M). Forested upland area was inundated at similar area increments in the \$10M and \$15M budget scenarios with approximately 50, 21, and 6 ha remaining after the 0.5, 1.0, and 1.5 m sea level rise scenarios, respectively (Figure 4). The proportion of developed/barren land inundated ranged from 13.7% (13.64 ha, \$20M–0.5 m) to 69.6% (37.72 ha, \$15M–1.5 m and 69.50 ha, \$20M–1.5 m; Table 5).

Figure 4: Area (ha) of land cover types present on optimized parcels under current mean higher high water (MHHW) and three future sea level rise scenarios (0.5 m, 1.0 m, and 1.5 m), grouped by budget scenario.

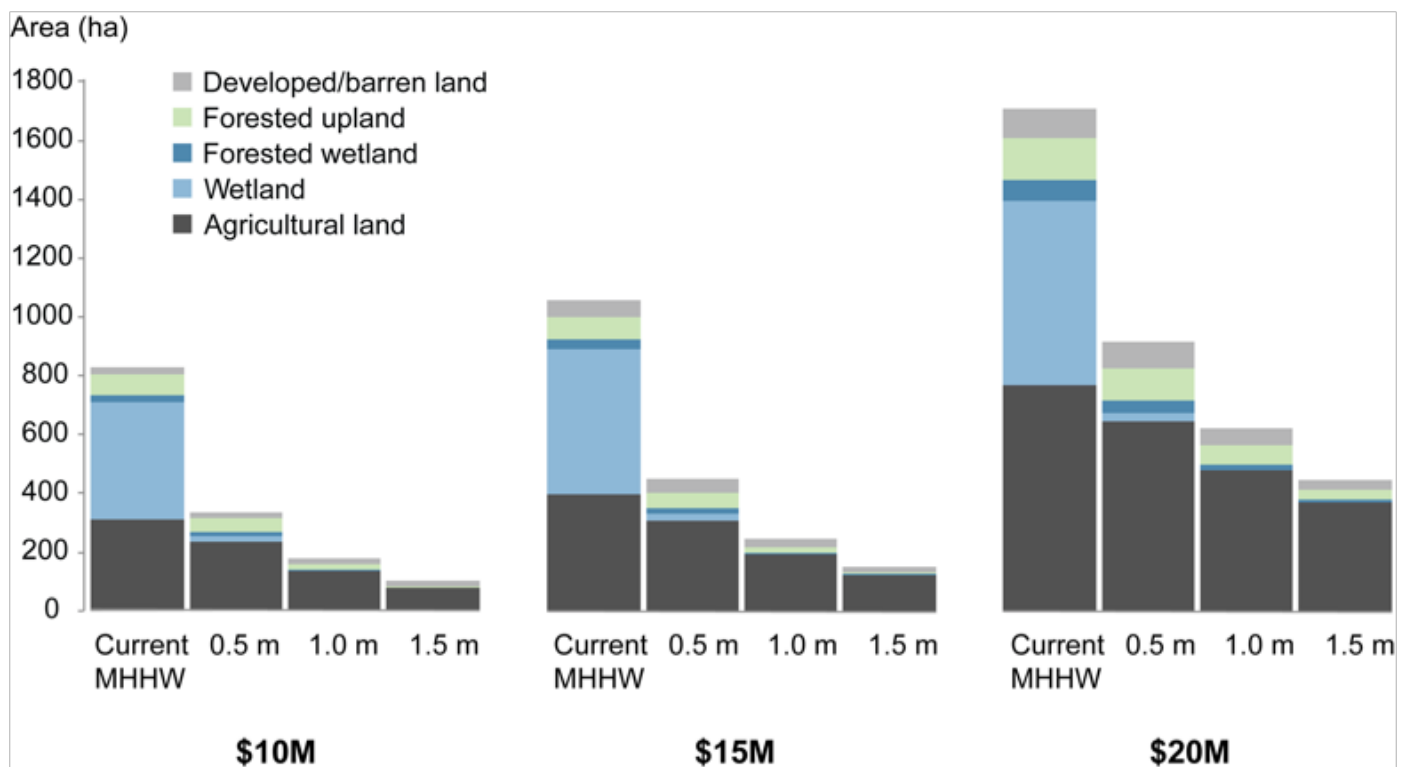


Table 5: Percent of area (ha) inundated relative to current MHHW by land cover type on optimized parcels for three sea level rise scenarios (0.5 m, 1.0 m, and 1.5 m).

Budget	Sea level rise scenario	Percent (%) of Total Area Inundated				
		Wetland	Forested wetland	Agricultural land	Forested upland	Developed /barren land
\$10M	0.5 m	96.3	36.8	23.9	30.9	14.5
	1.0 m	99.9	90.2	56.2	70.0	25.0
	1.5 m	100.0	99.3	74.5	92.2	37.5
\$15M	0.5 m	95.7	48.4	21.7	32.8	16.8
	1.0 m	99.9	91.4	51.1	71.8	60.0
	1.5 m	100.0	98.1	68.6	92.5	69.6
\$20M	0.5 m	95.1	39.9	16.1	24.0	13.7
	1.0 m	99.7	75.6	37.6	54.1	45.6
	1.5 m	99.9	85.6	51.6	77.2	69.6

Forested wetlands occupied less than 5% of the portfolio area in all budget and sea level rise scenarios. Forested wetland area ranged from 25.89 ha (\$10M) to 67.29 ha (\$20M) during current MHHW, and from 2.54 ha (\$10M) to 16.40 ha (\$20M) during the intermediate 1.0 m rise scenario (Figure 4). The average proportion of forested wetland area inundated across budget scenarios, was 41.7% with a 0.5 m rise in sea level, 85.7% with a 1.0 m rise, and 94.3% with a 1.5 m rise (Table 5).

DISCUSSION

Binary linear programming optimization outperformed benefit targeting by acquiring a greater conservation benefit across all budget scenarios. Optimization identified the best combination of unprotected tidal marsh parcels that maximized tidal marsh obligate breeding bird density for each budget constraint. At the \$10M level, the optimization model selected a portfolio of 18 parcels with unprotected salt marsh habitat for the protection of existing core tidal marsh bird populations for four species. The model conserved more marsh area (77 ha) and birds (319 tidal marsh obligate birds) than the benefit targeting model by selecting a more efficient combination of parcels and spending approximately \$60,000 more. Furthermore, for benefit targeting to achieve the conservation benefit secured by the optimization model, nearly \$2.9M in supplementary land acquisition funds would be required.

We found similar patterns in the magnitude and direction of the results for the portfolios from the \$15M and \$20M budget level analyses. When the two quantitative methods employed the same budget, optimization secured more birds and marsh area on more parcels than benefit targeting. Similar to the \$10M scenario, an additional \$2.7M and \$1.75M in supplemental funding is needed for benefit targeting to achieve what optimization did with \$15M and \$20M, respectively.

Based on these results and the results of other studies in the literature (Allen et al. 2011, Messer 2006, Messer and Allen 2010), we recommend that federal and state wildlife agencies and non-governmental conservation organizations employ optimization modeling to help evaluate land acquisition projects for wildlife conservation. Our study showed that optimization identified and prioritized a cost-effective set of projects, or parcels, that maximized overall conservation benefits in a quantitative and repeatable manner, while simultaneously allowing conservation planners to objectively make decisions about how to allocate limited funds. While this study evaluated one objective (maximizing bird density), mathematical programming can be used to identify cost-effective projects that meet multiple priority objectives, including competing objectives. Mathematical programming also provides conservation planners with the ability to incorporate important social objectives and constraints into the model,

such as landowners' "willingness to sell" and public support, information which can be obtained from surveys and public voting records. Even though consideration of the human component and its influence on achieving or failing to achieve conservation goals is paramount, most prioritization schemes fail to evaluate social data in the project selection process. Furthermore, sensitivity analyses can be simultaneously produced to help inform management and conservation planning decisions, especially with respect to real or perceived changes in land conservation and preservation budgets.

The application of optimization outside the realm of reserve site selection is growing, and recent literature highlights the innovative use of these algorithms to answer complex avian-specific management and conservation questions. Martin et al. (2007) used the optimal search algorithm Dijkstra to evaluate wintering American redstart (*Setophaga ruticilla*) populations and stable-isotope information. Downs et al. (2008) created a habitat suitability index model to determine nesting site carrying capacity for greater Sandhill cranes (*Grus canadensis tabida*), then modeled carrying capacity using a spatial optimization model (anti-covering problem) to determine the maximum number of pairs an area could support given a home range distance constraint. Stralberg et al. (2009) used a mixed integer programming approach to maximize marsh bird and waterbird abundance by identifying salt ponds for restoration.

In terms of tidal marsh conservation, optimization can be used to define abiotic features and biological community characteristics of target salt marshes to identify critical areas in need of protection that may double as smart investment choices in the face of marsh loss and alteration. Because Delaware is located almost entirely within the Coastal Plain, the state is vulnerable to impacts from global climate change, including projected coastal impacts of accelerated sea-level rise and increased storm frequency, and severity and associated wave velocities. Tidal marsh vulnerabilities to sea level rise were evident in our sea level rise evaluation where over 95% of wetlands on optimization-selected parcels were inundated in all scenarios. Similar projections of inundation hold for saltwater tidal wetlands throughout Delaware; 97% of the state's tidal wetland area will be inundated under 0.5

m of sea level rise and 99% under 1.0 and 1.5 m of sea level rise (Delaware DNREC 2012). However, inundation projections do not equate directly to marsh loss. Some marshes will be able to increase their elevation through natural accretionary processes and keep pace with rising sea levels. Recent models of coastal wetland resilience to sea level rise accounting for ecogeomorphic feedbacks (i.e., inundation, plant growth, organic matter accretion, and sediment deposition) project that marshes with intermediate suspended sediment concentrations will survive conservative sea level rise scenarios, but marshes will likely drown under more rapid accelerations (Kirwan et al. 2010).

Coastal marshes unable to naturally outpace rising seas through sufficient vertical accretion in their current locations will depend on opportunities for marsh migration, transgressing landward and upward over adjoining uplands, to survive (Cahoon et al. 2009). Forests, agricultural lands, and other undeveloped land cover types adjacent to tidal marshes will be necessary to provide opportunities for these wetlands to expand horizontally and migrate inland, given a gradual enough slope and no barriers to migration (e.g., paved surfaces, walls, dikes) (Cahoon et al. 2009). Therefore, information regarding the location of upland areas suitable for marsh migration is central to prepare for and facilitate future tidal marsh conservation.

In our sea level rise assessment of optimization-selected parcels, agricultural land had the greatest amount of area remaining of any land cover type after inundation in all sea level rise scenarios. The initial area of forested upland and developed/barren land was small compared to total wetland and agricultural land area. Portions of forested upland and developed/barren land were inundated in all scenarios, and the total area remaining in the most conservative sea level rise scenario (0.5 m) would support less than a fifth of the original wetland area in the \$10M and \$15M portfolios, and less than a third of the original wetland area in the \$20M portfolio, should marsh migration onto these upland areas be fully realized.

After sea level rise, agricultural lands accounted for at least 70% of the total land area in optimized parcels. If all agricultural land remaining in the \$10M and \$15M portfolios after inundation converted to tidal marsh then

in the 0.5 m sea level rise scenario, approximately 60% of the original wetland area would exist as transgressed tidal marsh. In the \$20M portfolio, converted agricultural lands would sustain 100% of the original wetland area. If sea levels rose 1.5 m by 2100 and all non-inundated agricultural lands converted to marsh, 20% and 25% of the original wetland area would remain in the \$10M and \$15M portfolios, respectively, and 60% of the original wetland area would remain in the \$20M portfolio. Given the results of our sea level rise evaluation, we conclude that when vertical accretion to sustain marsh areas in response to rising seas is not possible, marsh migration onto adjacent agricultural land provides the greatest opportunity for the persistence of tidal marshes and the continued support of core tidal marsh bird populations.

Existing wetland conservation programs on private lands, such as the Wetlands Reserve Program (WRP) and Wildlife Habitat Incentives Program (WHIP), provide landowners with funding for technical and financial support for conservation projects and could provide opportunities for tidal marsh conservation in the future. Both programs are authorized through the U.S. Farm Bill (Food, Conservation, and Energy Act of 2008) and administered by the U.S. Department of Agriculture's Natural Resources Conservation Service (NRCS). Through the WRP, landowners protect or enhance wetlands on their property, including restoring wetlands from former agriculture fields, and may be reimbursed up to 100% of conservation easement costs (NRCS 2008). The program is best "suited for frequently flooded agricultural lands, where planned restoration will maximize habitat for migratory birds and other wildlife, and improve water quality" (NRCS undated a). WHIP assists landowners in creating priority fish and wildlife habitat through cost-share agreements, and landowners may be reimbursed up to 90% of the costs (NRCS 2011). While the WRP and WHIP have been successful in creating and conserving habitat in and for the present, more incentives and long-term agreements are needed to bolster private landowners' voluntary program participation to ensure the future existence of habitats and associated species.

Working Lands for Wildlife, a new partnership between NRCS and U.S. Fish and Wildlife Service announced in September 2012, directly addresses conservation for

declining species on working agricultural lands and may be able to provide critical additional support for tidal marsh conservation in the future. The program provides technical and financial assistance through WHIP to farmers, ranchers, and forest owners to reverse declining populations of seven specific wildlife species (i.e., Bog turtle, Gopher tortoise, New England cottontail, Greater sage-grouse, Lesser prairie chicken, Southwestern willow flycatcher, and Golden-winged warbler) (NRCS undated b). Tidal marsh specialist species, such as Saltmarsh Sparrow, should be included in the Working Lands for Wildlife program to encourage conservation efforts in tidal marshes used as working agricultural lands (e.g., salt hay farms) and in other agricultural areas facing saltwater intrusion and encroachment by existing marsh habitat.

Considering predictions for the future of tidal marshes, current avenues for wetland conservation will need to take on new dimensions. A combination of programs like Working Lands for Wildlife and property rights tools such as rolling easements for marsh migration corridors will be needed to achieve conservation goals in the face of global climate change. Regardless of how conservation programs are supported, policies that provide opportunities for wetlands to migrate inland are likely to be less expensive and will have a greater probability of success if planning occurs before these lands are developed (Titus and Neumann 2009).

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Appendix D: Decision Support Tools – Connecticut case study

A proof-of-concept decision support tool for salt marsh conservation in Connecticut

Final report for award:

“Development of a Decision Support Tool for Coastal Habitats in Connecticut”

28th February 2012

Chris Field and Dr. Chris Elphick
Department of Ecology and Evolutionary Biology
University of Connecticut

Conservation practitioners in Connecticut are beginning to invest resources in decision support tools (DSTs) that will guide them in making sense of the bewildering array of options for land protection and restoration, especially along the coastline. One such tool, currently being developed by Fountains Spatial, is intended to guide the Long Island Sound Stewardship site selection process. Further development of a wildlife complement to this tool is a high priority for several organizations, including the State Department of Energy and the Environment (DEEP), Audubon Connecticut, and the Connecticut Audubon Society. This paper outlines a pilot DST to guide decisions for coastal bird conservation. At 2010's Connecticut “Avian Summit” – a meeting of representatives of most of the major organizations involved with bird conservation in the state – saltmarsh and beach-nesting birds were identified as a high conservation priority and, because data already exist for many species, a logical systems for which to develop a set of prototype DSTs. The prototype presented here is based on a systematic planning process (Margules and Pressey 2000). Following this science-based process will ensure that decisions based on the resulting tools are defensible, transparent, and based on the latest peer-reviewed evidence on how to make smart conservation decisions.

Saltmarsh and beach systems are complex, dynamic, and surrounded by uncertainty. Salt marshes in Connecticut are expected to undergo drastic changes in the next 100 years as sea levels continue to rise (Hoover 2010). One adaptation strategy, already being implemented by several conservation organizations, is to protect open space adjacent to salt marshes (often by purchasing the land outright) to create avenues for the potential landward migration of marshes. Because land prices in Connecticut are high, a successful implementation strategy will hinge on achieving efficiency in decision-making that will give the greatest conservation benefit per dollar spent. A challenge to achieving this efficiency is that land prices change with markets over time, and are not predictable with complete certainty. Therefore, the DST we have developed explicitly accounts for the uncertainty of how much it will cost to protect land, providing practitioners with the decision-making framework to

make low-risk, high-efficiency decisions.

Setting targets

In-person meetings to discuss quantitative conservation targets were held in early 2010 at the Center for Environmental Science and Engineering at the University of Connecticut, and in early 2011 at a breakout session during the Connecticut Conference on Natural Resources. These sessions were followed by surveys in which practitioners from CT DEEP and Audubon Connecticut ranked salt marsh and beach-nesting birds and their habitats in order of conservation priority. Using the results of these surveys, we narrowed the list of conservation targets to 5 species and 2 habitat types (Table 1). For each of the targets on this priority list, we developed three alternatives for quantitative population or habitat-area targets, and used a second survey to determine which target was favored by the stakeholder group.

DSTs were developed with the goal of protecting sufficient land to ensure that these quantitative targets are met. Given current population sizes, some targets are impossible to meet via protection alone, and will require active management for population growth (e.g., habitat restoration or creation) if they are to be achieved.

Table 1: Conservation targets and justification. Targets used for the prototype saltmarsh DST are highlighted in yellow.

	Target	Justification
Saltmarsh Sparrow	5000	minimum for population viability without regard to other states
Piping Plover	120	DEP current population target
Seaside Sparrow	1100	~ 1% of global population
Least Tern	50	~ half of current statewide population
migratory shorebirds	current population	
high marsh	715	half of current extent

For the prototype DST analysis, we focused on the two tidal marshes species, Saltmarsh Sparrows and Seaside Sparrows and conducted analyses to address the following questions: (1) Are all of the marsh

complexes for which comprehensive data exist needed to meet the target population sizes? (2) How much of the land at each of these marsh complexes is currently protected via land ownership or conservation easements? (3) Can land parcels at individual marshes be prioritized according to the trade off between conservation benefits versus economic cost of protection? Although beyond the scope of this contract, work on a DST focused on the beach-nesting priority species was also begun.

Data compilation

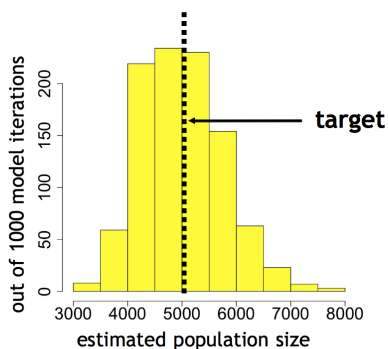
Sparrow abundance data were obtained from standardized point counts of tidal marsh birds (see Gjerdrum et al. 2008, Elphick et al. 2009, Meiman 2009). Land value data were compiled from the Town of Stonington's tax assessor and trulia.com. Additional data on beach-nesting birds were also compiled from the Connecticut DEEP's Piping Plover and Least Tern Recovery Project, although these were not used for the pilot tidal marsh DST.

Estimating priority bird species abundance

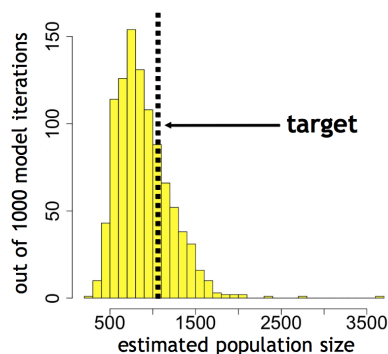
We analyzed the raw point count data using Bayesian hierarchical models to estimate marsh-level abundance of Saltmarsh and Seaside Sparrows for six major marsh complexes: Milford area; East River, Guilford/Madison; Hammonasset, Madison; Lower CT River; Bluff Point, Groton; and Barn Island, Stonington. For both species, the target statewide population size was within the estimated confidence intervals of the total population size for the 6 marsh complexes combined. This result suggests that these sites all need to be protected in order to meet the targets (Figure 1).

Figure 1. Estimated total population sizes for Saltmarsh and Seaside sparrows at the six marsh complexes studied. Each figure shows the results of 1000 simulated estimates based on analysis of point count data. Uncertainty causes each simulation to produce a different estimate, but collectively they show the range of likely population sizes, with the tallest bars indicating the most likely number. Dotted black bars indicate the target population size selected by Connecticut stakeholders.

Saltmarsh Sparrow population size - Barn Island, Bluff Point, Lower CT River, East River, Hammonasset, Milford



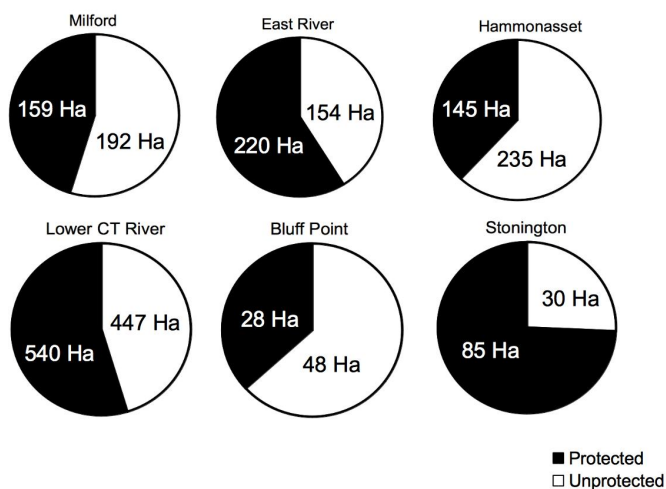
Seaside Sparrow population size - Barn Island, Bluff Point, Lower CT River, East River, Hammonasset, Milford



Current protected status of salt marshes

We determined the proportion of total marsh habitat in the six major marsh complexes that is under some kind of protected status (i.e., conservation easement or in conservation ownership) using DEEP's Connecticut Parcels for Protected Open Space Mapping (POSM) database and data from the U.S. Geological Survey's GAP analysis program (<http://gapanalysis.usgs.gov/>). For this initial analysis, we did not include land that is simply protected by the existence of wetland legislation. The protected status of Connecticut's marshes is variable, with Stonington's Barn Island closest to being fully protected (Figure 2).

Figure 2: The proportion of marsh habitat under protection at six major marsh complexes.



Incorporating land costs

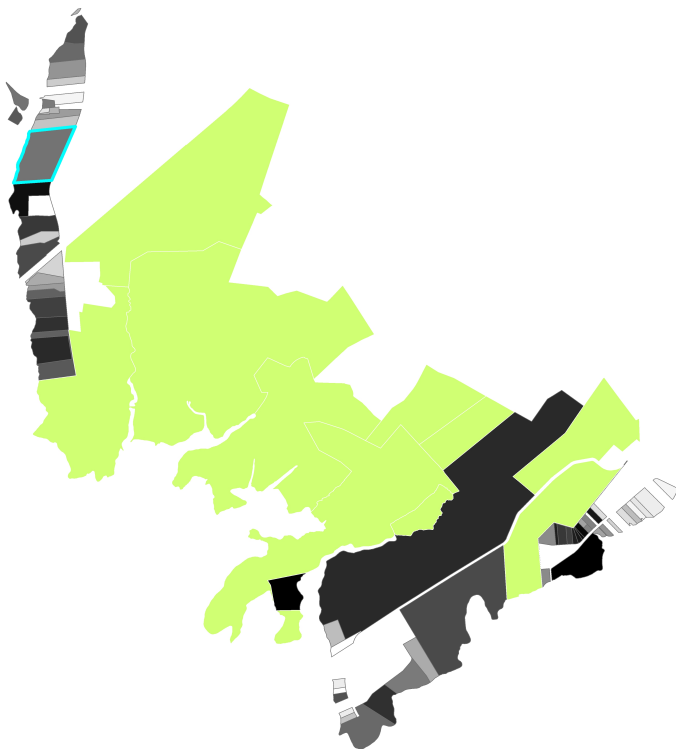
To help guide management decisions we developed a method for prioritizing land parcels based on the trade-off between their cost and their conservation benefits. We implemented this method for the marshes at Barn Island to illustrate the approach and demonstrate its utility. For each tax parcel in this marsh complex, we compiled two pieces of information: 1) the total area of high and low marsh, calculated using a raster developed by Hoover (2010)

and 2) the assessed value of the property from the Town of Stonington's Tax Assessor. Because information from the assessor's office does not reflect the most up-to-date property values, we also conducted a regression-based economic analysis of recent land sales in Stonington using information from trulia.com. From these analyses we estimated that Stonington's overall housing market has likely declined by ~30% since properties were last assessed, and that 95% of properties were sold within the range of $\pm 20\%$ of market value. By combining the assessed values with the estimated market change we were able to estimate both the current market value and uncertainty in that value (i.e., $\pm 20\%$) for each parcel.

Prioritization using the “fraction of the spares”

We determined that the “fraction of the spares” (FOS) conservation index (Phillips et al. 2011) was the most flexible way to identify which tax parcels were the highest priorities for acquisition. The FOS is conceptually simple and computationally inexpensive, which makes it possible to easily recalculate the index to keep up-to-date with changing land markets and the most recent conservation actions. We calculated the FOS for each parcel in the Barn Island complex, and ranked parcels according to their relative contributions to our targets based on the area of high and low marsh in each parcel. These values were then prorated by dividing the FOS value by the cost of purchasing the parcel, in effect turning the index into a cost/benefit ratio. This ratio was calculated for every parcel in Stonington that contained marsh habitat. The uncertainty of the likely sales price (represented by the $\pm 20\%$ interval around the market value) was propagated in the calculation of the index, resulting in FOS values with 95% confidence intervals. The mean FOS values are shown in Figure 3.

Figure 3: Preliminary prioritization of parcels in Stonington, CT. Green parcels have already been protected via purchase or easement; grey-scale parcels are under consideration for purchase, with darker colors representing higher priority scores using the FOS method described in this report. The parcel outlined in blue was recently purchased.



Conclusions and Next Steps

The approach we have developed is purposefully very flexible, easy to calculate and understand, and based on the latest research in conservation biology and decision theory. We have deliberately applied the approach to a simple example with a small set of conservation targets and a single conservation action in order to illustrate the method as a “proof-of-concept”. The approach, however, can easily be expanded or applied to other systems by including a larger set of targets and considering a wider range of conservation actions (e.g., restoration), or even explicitly trading-off the costs and benefits of alternative conservation actions. It also would be possible to combine information from disparate areas of conservation (e.g., by examining the trade-offs between conservation actions for beach-nesting birds vs. tidal marsh birds). An additional extension of the current model would be to include incorporate information on each parcel's vulnerability to development in the calculation of the FOS, which would shift conservation priority to those parcels that are most vulnerable in the short term.

Now that a working prototype has been developed, we anticipate that the next stages will be to extend the analysis to a statewide scale and to incorporate predictions of future marsh distributions. Doing this would make it possible to prioritize purchase of land parcels in order to most efficiently ensure that marshes are capable of migrating landward (naturally or with assistance) in the long-term. Most of Connecticut's tidal marshes are protected by strong legislation for wetland protection, but potential areas for landward migration are not, and for the next several decades these sites will likely be the main focus of attention for salt marsh conservation in the state.

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