

Shorebird Response to Spatiotemporal Variability in  
non-Tidal Wetlands in the Sacramento Valley

by

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Dissertation submitted in partial fulfillment of  
the requirements for the degree of Doctor  
of Philosophy in the Department of  
Environment in the Graduate School  
of Duke University

2018

ABSTRACT

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## **Abstract**

Over 50% of Western Hemisphere shorebird species are in decline due to ongoing habitat loss and degradation. Many shorebird species require flooded habitat to rest and feed during migratory movements spanning thousands of miles between breeding and wintering grounds every spring and fall. In particular, shorebirds require shallowly flooded habitat (water depth <15cm deep)—due to their morphology (i.e., bill and tarsus length), many species are excluded from exploiting invertebrate prey resources in deeper waters. While habitat-associations for shorebirds are relatively well understood from observational studies, the distribution of suitable shorebird habitat over the broad areas used by these species during migration is not well described. In some regions of high wetland loss, shorebirds are heavily reliant on a core network of remaining human-managed wetlands and flood-irrigated agricultural fields. Refuges also provide substantial flooded habitat resources; however, these have typically been designed and managed to match the habitat needs of waterfowl, which can use much deeper water than shorebirds. Effective conservation strategies for migratory shorebirds will require improved understanding of flooded habitat suitability patterns over large migratory pathways, as well as knowledge of how species respond to habitat fluctuations over time.

We analyzed water extent dynamics across the Sacramento Valley of California, a globally important shorebird stopover site, for a 1983-2015 Landsat time series, and evaluated the effect of climate on water extent. Satellite measurements of surface water offer promise for understanding wetland habitat availability at broad spatial and temporal scales. A range of methods can detect open water from imagery, including supervised classification approaches and thresholds for spectral bands and indices. Thresholds provide a time advantage; however, there is no universally superior index, nor single best threshold for all instances. We used random forest to model the presence or absence of water from >6,200 reference pixels, and derived an optimal water probability threshold for our study area using receiver operating characteristic curves. An optimized mid-infrared (1.5–1.7  $\mu\text{m}$ ) threshold identified open water in the Sacramento Valley of California at 30-m resolution with an average of 90% producer's accuracy, comparable to approaches that require more intensive user input. SLC-off Landsat 7 imagery was integrated by applying a customized interpolation that mapped water in missing data gaps with 99% user's accuracy. On average we detected open water on ~26,000 ha (~3% of the study area) in early April at the peak of shorebird migration, while water extent increased five-fold after the migration rush. Over the last three decades, late March water extent declined by ~1,300 ha per year, primarily due to changes in the extent and timing of agricultural flood-irrigation. Water within shorebird habitats was significantly associated with an index of water availability at the peak of

migration. Our approach can be used to optimize thresholds for time series analysis and near-real-time mapping in other regions, and requires only marginally more time than generating a confusion matrix.

Two dimensional representations of flooded habitat are insufficient to capture dynamic changes within the narrow water depth range that is effectively accessible to migratory shorebirds. We developed a method to quantify shallow water habitat distributions in inland non-tidal wetlands, and assessed how water management practices have affected the amount of shorebird habitat in Sacramento National Wildlife Refuge Complex (SNWRC), California. We produced water depth distributions and modeled optimal habitat (<10 cm deep) within 23 managed wetlands using high-resolution topography and fixed-point water depth records. We also demonstrated that habitat availability, specifically suitable water depth ranges, can be tracked from satellite imagery and high-resolution topography. We found that wetlands with lower topographic roughness may have a higher potential to provide shorebird habitat and that strategically reducing water levels could increase habitat extent. Over 50% of the wetlands measured provided optimal habitat across <10% of their area at the peak of migration in early April, and most provided a brief duration of shallow water habitat. Reducing water volumes could increase the proportion of optimal habitat by 1– 1,678% (mean = 294 %) compared to actual volumes measured at peak spring migration in 2016. For wetlands with a high habitat potential, beginning wetland drawdown earlier and

extending drawdown time could dramatically improve habitat conditions at the peak of shorebird migration. Our approach can be adapted to track dynamic hydrologic changes at broader spatial scales as additional high-resolution topographic (e.g., lidar, drone imagery photogrammetry) and optical remote sensing data (e.g., Planet imagery, drone photography) become available.

Attempting to model the response of a community of shorebird species to flooded habitat dynamics from local to landscape scale necessitates a rich dataset including field observations of shorebird habitat use as well as information regarding regional habitat conditions over multiple time periods. Bringing together these data sources results in several challenges for classical statistical approaches, including overdispersion, fixed and random effects due to repeated measures, irregular temporal intervals, and missing data. We investigated how spring migration habitat use by 19 shorebird species at 327 wetland survey locations across SNWRC responded to flooded habitat fluctuations at multiple spatial scales from 1997-2015 using a generalized joint attribute modelling approach. In this analysis, we integrated shorebird census records and habitat conditions documented in the field with a suite of landscape-level habitat measurements derived from satellite imagery, as well as water availability, water allocation and land use information. We found that abundance by species peaked in late March and early April at SNWRC. Shorebird abundance responded positively to the amount of flooded habitat at a given wetland survey location. The total amount of water

detected was the most important landscape habitat measure; shorebirds were less likely to be observed at high abundance at SNWRC wetlands when greater flooded habitat extent was present on the surrounding landscape. We found that human land and water management were influential drivers of shorebird habitat use. Water allocation information and reservoir storage resulted in better model fit (i.e., lower DIC) than including measures of surface water availability or drought conditions. Furthermore, the amount of landscape flooded habitat on agricultural land produced a better fit than considering all flooded habitat, or flooded habitat detected in wetlands. We found that the most relevant scale for measuring landscape flooded habitat was within 2-10 km of wetland survey locations; this distance could be a useful guideline for monitoring habitat conditions and targeting creation of supplemental habitat to bolster the existing wetland network in the Sacramento Valley.

## Dedication

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# Contents

Abstract .....	iv
List of Tables .....	xiv
List of Figures .....	xv
Acknowledgements .....	xvii
1. Introduction .....	1
2. Three decades of Landsat-derived spring surface water dynamics in an agricultural wetland mosaic; implications for migratory shorebirds .....	1
2.1 Introduction.....	1
2.2 Data and Methods .....	6
2.2.1 Study area.....	6
2.2.2 Analysis Tools.....	9
2.2.3 Landsat time series.....	10
2.2.4 Comparison of methods to identify water vs. non-water.....	12
2.2.5 Optimized water/non-water threshold development.....	14
2.2.6 Time series image processing .....	17
2.2.7 Spatiotemporal analysis of shorebird habitat.....	18
2.3 Results .....	20
2.3.1 Comparison of methods to identify water vs. non-water.....	20
2.3.2 Evaluation of optimized spring water/non-water mid-infrared threshold .....	22
2.3.3 Effectiveness of IDW interpolation for SLC-off Landsat 7 classifications.....	26
2.3.4 Landsat-derived spring open water dynamics .....	26

2.4 Discussion.....	36
2.5 Conclusions .....	42
3. Quantifying shorebird habitat in managed wetlands by modeling shallow water depth dynamics .....	44
3.1 Introduction.....	44
3.2 Methods .....	50
3.2.1 Study area.....	50
3.2.2 Site selection.....	54
3.2.3 Water depth monitoring.....	57
3.2.4 High-resolution topography mapping.....	57
3.2.5 Daily spring water depth and optimal habitat modeling.....	58
3.2.6 Assessing potential for shallow water habitat gains through water management.....	61
3.2.7 Modeling historical peak migration habitat over drought cycles using satellite imagery .....	62
3.3 Results .....	64
3.3.1 Habitat suitability patterns during spring shorebird migration .....	64
3.3.2 Simulated water management to maximize the proportion of optimal shorebird habitat .....	65
3.3.3 Historical peak migration habitat distributions over drought cycles .....	69
3.4 Discussion.....	72
3.5 Conclusions .....	78
4. Shorebird response to climate, water and land management at multiple scales during spring migration, Sacramento Valley of California, 1997 – 2015.....	80

4.1 Introduction.....	80
4.2 Methods .....	87
4.2.1 Study area.....	87
4.2.2 Shorebird census records from SNWRC wetlands.....	89
4.2.3 Water and vegetation management at SNWRC wetland survey locations .....	93
4.2.4 Regional flooded habitat and vegetation conditions.....	93
4.2.5 Regional water availability and water allocation data:.....	95
4.2.6 GJAM modelling.....	96
4.2.7 Modelling shorebird abundance by species .....	99
4.3 Results .....	102
4.3.1 Shorebird response to local and regional habitat conditions, and time within spring .....	102
4.3.2 Interactions between water extent and spring period (Model 2) .....	107
4.3.3 Effect of water availability and water allocations (Model 3-7) .....	107
4.3.4 Effect of land use of flooded habitat (Models 8-9).....	108
4.3.5 Scale of shorebird response to landscape water extent (Models 10-13).....	108
4.4 Discussion.....	109
4.5 Conclusion.....	114
5. Conclusion .....	115
5.1 Methodological contributions.....	115
5.2 Findings and recommendations.....	116
5.3 Future work.....	118

Appendix A. Supplementary material for Three decades of Landsat-derived surface water dynamics in an agricultural wetland mosaic; implications for migratory shorebirds.....	120
Appendix A.1 Spatial assessment of Landsat image quality in the study area.....	120
Appendix A.2 Random forest models used for threshold identification for a single Landsat image.....	121
Appendix A.3 Comparison of prediction maps for multiple water/non-water classification methods.....	124
Appendix A.4 Water extent variability within the spring season.....	126
Appendix B. Supplementary material for Quantifying shorebird habitat in managed wetlands by modeling shallow water depth dynamics.....	127
Appendix C. Supplementary material for Shorebird response to climate, water and land management at multiple scales during spring migration, Sacramento Valley of California, 1997 – 2015.....	130
Appendix C.1 Predicted abundance and diversity of shorebirds for Model 1.....	130
Appendix C.2 Results for questions about shorebird habitat use drivers from GJAM Models 2-13. ....	133
References .....	140
Biography.....	158

## List of Tables

Table 1: Surface reflectance datasets and reference data sources for confirmed water and non-water locations in the Sacramento Valley of California. ....	16
Table 2: Assessment of multiple methods to classify open water.....	21
Table 3: Identification of a mid-infrared surface reflectance threshold to map water. ....	25
Table 4: Shorebird species documented by the census at Sacramento National Wildlife Refuge Complex.....	91
Table 5: Predictor variables used in models of shorebird abundance by species.....	98
Table 6: Summary of shorebird abundance models.....	101
Table 7: Significance of response by species to predictors included in Model 1.. ....	106

## List of Figures

Figure 1: Land use and land cover in the Sacramento Valley. ....	9
Figure 2: Landsat surface reflectance data availability and quality. ....	11
Figure 3: Example of inverse distance weighted interpolation. ....	18
Figure 4: Receiver operating characteristic (ROC) curves summarizing nine-fold cross validation of water/non-water random forest models. ....	23
Figure 5: Long-term spring water extent trends from 1983 – 2015. ....	28
Figure 6: Spring water extent and variability by two-week period, 1983 – 2015. ....	29
Figure 7: Water extent and frequency for spring months in the Sacramento Valley. ....	31
Figure 8: Relativized estimates of spring water frequency within flood-irrigated agriculture and herbaceous wetlands. ....	33
Figure 9: Annual water availability and spring water extent. ....	34
Figure 10: Landcover and land use in the Sacramento Valley of California. ....	53
Figure 11: Monitored wetlands in Sacramento National Wildlife Refuge Complex. ....	55
Figure 12: Example of using high-resolution elevation and water depth measurements collected by a sensor at a fixed location to infer daily spatial water depth and optimal habitat distributions. ....	60
Figure 13: Temporal mismatch between peak shorebird migration and the timing of shallow water habitat availability. ....	65
Figure 14: Association between the maximum proportion of optimal shorebird habitat (<10 cm water depth) observed across 23 wetlands and wetland topography and optimal water volume. ....	67
Figure 15: Implications of water level management and topographic variation for optimal shorebird habitat distributions. ....	68

Figure 16: Example of using satellite-based water extent mapping and high-resolution topography data to model optimal habitat distributions.....	71
Figure 17: Study locations in Sacramento National Wildlife Refuge Complex. ....	88
Figure 18: Mean and standard error of sensitivity across shorebird species to spring period and quantitative habitat predictors in Model 1.....	103
Figure 19: Response by species to spring periods in Model 1. ....	104

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# 1. Introduction

Given that most migratory shorebird species are entirely dependent on wetlands for food and rest during long-distance journeys in the spring and fall (Brown et al. 2001), they are considered to be indicators for the health of wetland systems (Sutherland et al. 2012), which provide ecosystem services ranging from water, food and habitat provision, to waste treatment and greenhouse gas regulation (Costanza et al. 1997, 2014). Migratory shorebirds face interacting threats of habitat loss and climate change (Davidson, 2014; Galbraith, DesRochers, Brown, & Reed, 2014; Morrison et al., 2006), with population declines reported for over half of the 75 shorebird species in the Western Hemisphere (Brown, et al., 2001). Effective conservation action requires habitat suitability information over large migratory pathways, and an understanding of the scaling of species responses to changes in the habitat network over time.

Shorebird habitat use during migration may be influenced by multiple factors. At broad geographical scales, habitat use is driven by evolutionary biology and the habitat choices of previous successful breeding individuals as well as the extent and configuration of flooded habitat (Elphick 2008, Webb et al. 2010). Yet shorebirds also respond to attributes that change over smaller spatial scales, including invertebrate prey densities (Colwell and Landrum 1993, Farmer and Wiens 1999), vegetation (Colwell 2010, Ma et al. 2010, Stutzman 2012), competition, and the presence of predators (Hutto

1985, Deppe and Rotenberry 2008, Zharikov et al. 2008, Stutzman 2012). In practice, habitat quantity is limited by accessibility, given water depth distributions and bird morphology (i.e., bill and tarsus length; Collazo et al. 2002, Strum et al. 2013). Most shorebirds are limited to using flooded regions <15 cm deep, but smaller shorebirds may be restricted to using <5 cm deep water (Collazo et al. 2002, Taft et al. 2002, Ma et al. 2010). Current wisdom suggests that maintaining complexes of many wetlands with variable water depth will support high wetland-dependent bird diversity (Ma, et al., 2009; Taft, et al., 2002; Webb, et al., 2010).

Fluctuations in flooded habitat extent and suitability can be strongly driven by seasonal and year-to-year climate variation, and will be affected by ongoing climate change. For example, the El-Niño Southern Oscillation (Feldl and Roe 2011) brings episodic extreme wet conditions to the normally semi-arid central section of the North American Pacific Flyway. Wetter conditions can result in more shallow water habitat at the margins of deeper wetlands, yet may increase water depths in normally shallow wetland, making them too deep for shorebird access. More arid inland regions with isolated wetlands are subject to substantial seasonal variation in flooded habitat presence and water depth ranges (Central Valley Joint Venture 2006). Climate change will likely make isolated non-tidal wetlands habitats less reliable due to increased

drought severity, while sea-level rise may make some coastal wetlands inaccessible to shorebirds (Galbraith et al., 2002; Werner, Johnson, & Guntenspergen, 2013).

Human land and water use decisions can also affect flooded habitat distributions, especially for semi-arid and arid regions with heavily modified wetland networks. For example, most wetland habitat in California's Central Valley (>90% wetland loss; Frayer et al. 1989) is now human-manipulated, rather than being driven by natural hydrologic patterns (Central Valley Joint Venture 2006). Most remaining semi-natural wetlands in the Central Valley are managed by federal and state agencies, and important surrogate wetland habitat is also available in flood-irrigated rice fields (Elphick 2000, 2010, Barbaree et al. 2015). Where flood-irrigated agriculture represents a large portion of the landscape at shorebird stopovers, irrigation systems and timing, crop choices, and other land management decisions can directly affect the amount of shorebird habitat.

Despite the obvious importance of freshwater, which is present over <1% of the Earth's surface, this resource is still poorly monitored and managed globally (Alsdorf et al. 2007, Turpie et al. 2015). This is particularly true of wetland systems and agricultural lands, which are not well-represented in in-situ monitoring datasets used to validate global surface water measurements (Pimentel et al. 2004, Alsdorf et al. 2007). Even in California's highly engineered water resources system, allocations exceed surface water

supplies by as much as 1,000% (Jenkins et al. 2004, Grantham and Viers 2014). Satellite remote sensing has played a key role in improving information regarding surface water distributions and how they are changing under increased human modification (Alsdorf et al. 2007, Turpie et al. 2015).

Remote sensing advancements have recently enabled a move from static, or short-term assessments of flood extent at coarse resolution (e.g., Prigent et al. 2007, Papa et al. 2010, 25-km grid cells) to tracking global hydrologic dynamics at relatively fine-grained resolution from satellite imagery (Alsdorf et al. 2007, Pekel et al. 2016). Given that more intensive field measurements of surface water condition are not available over broad areas, the presence and duration of flooding can be informative for assessing shorebird habitat suitability (Farmer and Parent 1997, Elphick 2008, Reiter et al. 2015). Landsat imagery documents conditions at 30-m resolution for the same location every ~8-16 days, and it's >30 year historical record permits assessing trends across precipitation frequency and intensity changes induced by cycles such as El Niño (Hurrell and Loon 1997, Feldl and Roe 2011). Numerous well-established methods are available to identify and characterize wetlands, including supervised maximum likelihood (Mather 1985, Ozesmi and Bauer 2002), and classification tree approaches (Friedl and Brodley 1997, Breiman 2001, Baker et al. 2006, Tulbure and Broich 2013). Indices such as the normalized difference water index (NDWI; McFeeters 1996),

modified normalized difference water index (MNDWI; Xu, 2006), automated water extraction index (AWEI; Feyisa et al. 2014) and Tasseled Cap wetness index (Crist and Cicone 1984) can also be used to characterize moisture gradations and classify flooded regions.

Although water extent and flood duration information provide a proxy for habitat suitability for wetland-dependent species (Reiter et al. 2015, Schaffer-Smith et al. 2017), optical remote sensing data does not provide water depth information (Alsdorf et al. 2007, Turpie et al. 2015). Water depth can be directly measured in a variety of ways, including visual monitoring of depth gauges (Strum et al. 2013), or the use of instruments such as water-level loggers or capacitance sensors (Larson and Runyan 2009), but these measurements are limited to a fixed point location at the in-situ sensor. Mapping water depth across wetlands over broad areas requires knowledge of water surface elevations as well as the underlying topography; however, topographic data with low vertical measurement error is not yet widely available.

The relatively low vertical accuracy of existing digital elevation models (DEMs) and the dearth of topographic data for inland non-tidal wetland systems currently limits our ability to resolve shorebird habitat suitability. Neither the 30-m global elevation dataset (average absolute vertical accuracy of 9 m over the continental U.S.; Tachikawa et al. 2011), or the 10-m U.S. National Elevation Dataset (average absolute vertical

accuracy of 1.55 m; U.S. Geological Survey 2015) is sufficient for estimating water depth fluctuations on the order of centimeters. Unfortunately, most DEM products, including those relying on topographic lidar, also completely omit regions that were flooded at the time of data acquisition, considering them as flat regions with a single elevation value (Alsdorf et al. 2007). Differential GPS topography surveys (Los Huertos and Smith 2013) can produce elevations with suitable vertical accuracy for modelling water depth spatially at a fine-scale within individual wetlands lacking other available high-resolution topographic data. The integration of mapped topography with either precise field measurements of water depth or satellite-derived water extent information can provide information regarding the presence and frequency of flooding within specific water depth ranges (Rowe et al. 2002, Munyaneza et al. 2009). Tracking fine-scale spatiotemporal water depth distributions can assist in understanding the implications of climate, water and land use for shorebird habitat suitability.

Although species-habitat relationships for shorebirds have been studied extensively in the short-term for localized study areas, in most cases they are not well-documented over large areas or long time scales. Assessing long-term shorebird response to wetland habitat dynamics along migration pathways requires documentation of shorebird habitat use at multiple time points, as well as measures of landscape flooded habitat extent and variability, climate, and human management of

land and water matching shorebird observations. Traditional species distribution (e.g., Guisan and Zimmermann 2000) and abundance modelling approaches (e.g., Potts and Elith 2006) are not ideally suited for analyzing such diverse datasets, collected at multiple spatial and temporal scales. For example, shorebird census data are characterized by extreme overdispersion, and capture only those migrating individuals that happen to be transiting the area being observed at the time of surveys. Replication in space and time for species abundance and predictor information results in both fixed and random effects that pose unique challenges for statistical analysis (Bolduc and Afton 2008). For example, these characteristics violate the assumptions of most regression-based models (McCullagh and Nelder 1989, Wintle and Bardos 2006). Extreme overdispersion has been previously accounted for in species distribution (Potts and Elith 2006) and abundance models (Fletcher et al. 2005), yet these methods still cannot accommodate irregular temporal data or missing data, and they also cannot simultaneously examine the responses of multiple species in a community. Landscape habitat variables derived from satellite-imagery are subject to missing observations, due to cloud cover. Shorebird census observations used to measure the response in terms of habitat use may be temporally irregular and suffer from missing data, for example due to weather conditions prohibiting surveys. Suitable modelling approaches are needed that can examine the response of multiple shorebird species in the community jointly, in

relation to multiple habitat covariates, accounting for irregular temporal dimensions, and observations with missing data.

## **2. Three decades of Landsat-derived spring surface water dynamics in an agricultural wetland mosaic; implications for migratory shorebirds**

### ***2.1 Introduction***

Freshwater resources provide benefits to human and natural communities ranging from water, food and habitat provision, to waste treatment and greenhouse gas regulation; yet these critical resources are limited to <1% of the Earth's surface. Despite this small areal extent, there are substantial gaps in our knowledge of the distribution and variability of terrestrial surface water resources over time (Alsdorf et al. 2007, Turpie et al. 2015). Freshwater is poorly monitored and managed across the globe, especially with regard to wetlands and water applied to agricultural lands (Pimentel et al. 2004, Alsdorf et al. 2007). Even in California, which has one of the most highly engineered and intensively managed water systems in the U.S., water rights in some areas represent 1,000% of the surface water supply (Jenkins et al. 2004, Grantham and Viers 2014). Recent pronounced droughts highlight the added complexity of management under climate change interacting with human-imposed water stress, particularly in arid regions with high rates of wetland conversion (Maggioni 2015, Van Loon et al. 2016).

Over half of the 75 shorebird species in the Western Hemisphere are in decline (Brown et al. 2001), indicating that wetland networks are in peril. Most migratory

shorebird species are entirely dependent on wetlands for food and rest during long-distance journeys in the spring and fall (Brown et al. 2001); many face dual threats of habitat loss and climate change (Morrison et al. 2006, Davidson 2014). Under ongoing climate change, inland non-tidal wetlands are at increased risk from future drought severity, and they will increase in importance for migratory shorebirds when sea level rise reduces access to coastal wetlands (Galbraith et al. 2002, Werner et al. 2013). To safeguard migratory flyways into the future, improved understanding of long-term wetland extent and variability over large areas is needed, as well as insight into the capacity for these systems to tolerate changes in water availability (Dudgeon et al. 2005, Turpie et al. 2015).

Satellite remote sensing is key to understanding surface water resources and how they are responding to intensified appropriation and modification by humans (Alsdorf et al. 2007, Turpie et al. 2015). In recent years, several global inundation analyses have been released that have moved from static, coarse scale (>1 km) products (e.g., Lehner and Döll 2004, Bontemps et al. 2011, Verpoorter et al. 2014) to more dynamic offerings, such as the Global Inundation Extent from Multi-Satellites (Fluet-Chouinard et al. 2015) and the MODIS water mask (Carroll et al. 2009). Studies of wetland dynamics at global scales have typically focused on relatively short time periods with coarse spatial resolution (e.g., Prigent et al. 2007, Papa et al. 2010; 25-km grid cells), and therefore have

been unable to capture smaller wetland features, or account for longer term cyclical hydrologic variability.

Landsat Thematic Mapper imagery can be used to map open water at 30-m resolution (Baker et al. 2006, Alsdorf et al. 2007) appropriate for resolving smaller, shallow wetlands that provide important migratory shorebird habitat (Strum et al. 2013). There is great potential for tracking long-term surface water dynamics given Landsat's <16-day revisit period from 1983 to the present (e.g., Mueller et al. 2016, Feng et al. 2016, Tulbure et al. 2016). The presence and duration of flooding can be informative in lieu of more intensive field measurements (Farmer and Parent 1997, Elphick 2008, Reiter et al. 2015). For example, these attributes influence invertebrate prey densities, which are challenging to measure precisely in situ over large areas (Batzler 2013). Landsat's historical timespan permits analysis of multiple El Niño cycles, which strongly influence the frequency and intensity of precipitation for many regions, including the western U.S. (Hurrell and Loon 1997, Feldl and Roe 2011). An analysis of the spatiotemporal variability of surface water at migratory stopover sites is needed to better understand baseline habitat conditions, particularly in regions with extreme seasonal and interannual variability.

Various approaches to identify surface water based on satellite imagery have been developed. Unsupervised classification approaches have been the most common

technique in the past for mapping wetlands (Ozesmi and Bauer 2002). Of the many supervised classification methods available, maximum likelihood has been used most frequently (Mather 1985, Ozesmi and Bauer 2002), however classification trees have become increasingly popular, and typically produce superior results (Friedl and Brodley 1997, Breiman 2001, Baker et al. 2006, Tulbure and Broich 2013). Thresholds can also be used for land cover mapping, with an advantage of lower overall investment for the user; once developed, a classification can be generated virtually instantaneously (Friedl and Brodley 1997, Chuvieco 2016). Thresholds can be identified from individual multi-spectral bands as well as water indices such as the normalized difference water index (NDWI; McFeeters 1996), modified normalized difference water index (MNDWI; Xu, 2006), automated water extraction index (AWEI; Feyisa et al. 2014) and Tasseled Cap wetness index (Crist and Cicone 1984).

These water indices have variable performance depending on scene conditions and study area extent (Yang et al. 2015, Fisher et al. 2016); thresholds also vary in time and space (Friedl and Brodley 1997). Thorough comparisons of multiple indices have been limited to a handful of studies (Ji et al. 2009, Campos et al. 2012, Fisher et al. 2016) with no clear best index for global application. Previous research indicates that thresholds should be modified for local conditions (Xu 2006, Feyisa et al. 2014), yet few studies provide guidance for appropriate threshold optimization methods. A recent

study by Campos et al. (2012) used the mean and standard deviation of values across 12 monthly images to select a threshold, while others have used omission and commission error as the basis of threshold selection (Yang et al. 2015, Fisher et al. 2016). Sheng et al. (2016) used iterative segmentation to identify NDWI thresholds for mapping lakes in Oceania. Ji et al. (2009) used spectral unmixing of pure pixels derived in a lab setting to suggest default thresholds for different fractional water coverages (starting points for 25, 50, 75, 100% water cover). Some of these studies remain untested outside of lab conditions (Ji et al. 2009), while others incorporate more field validation points than is normally practical (Fisher et al. 2016). Most studies do not explicitly evaluate accuracy outside of the source regions and dates used to train water classifications (Campos et al. 2012, Feyisa et al. 2014, Fisher et al. 2016, Sheng et al. 2016), which is of particular import for time series analysis.

This study used the entire Landsat thematic mapper time series (1983-2015) to evaluate water distribution patterns during spring shorebird migration in the Sacramento Valley of California, a globally important wetland stopover (Western Hemisphere Shorebird Reserve Network 2009). Previously published water mapping work in this system over shorter timescales (<10 years) has employed Landsat in both unsupervised and supervised classifications (Spell et al. 1995, Reiter and Liu 2011, Reiter et al. 2015). Classification and change detection procedures must be efficient if applied

across an extensive time series, and retain a satisfactory level of accuracy. The objectives of this study were to: 1) develop a reproducible approach to optimize a threshold that accurately identifies open water from the Landsat surface reflectance time series, 2) compare this approach to other methods typically used in mapping water, and 3) assess spatial and temporal patterns of open water from the historical record to inform water and wetland management. Hereafter we use water to refer to areas where open water, unobscured by vegetation, was present and non-water to refer to regions where open water was not detected.

## **2.2 Data and Methods**

We first built a Landsat surface reflectance time series for cloud-free, non-urban areas from 1983-2015. We then tested different spectral and water index thresholds against supervised classification methods, and subsequently identified an overall spring water/non-water threshold using extensive reference data for validation. Finally, we applied the optimized spring threshold for classification of open water from the 32-year time series, and analyzed spatiotemporal patterns and climate sensitivity of water within important migratory shorebird habitat.

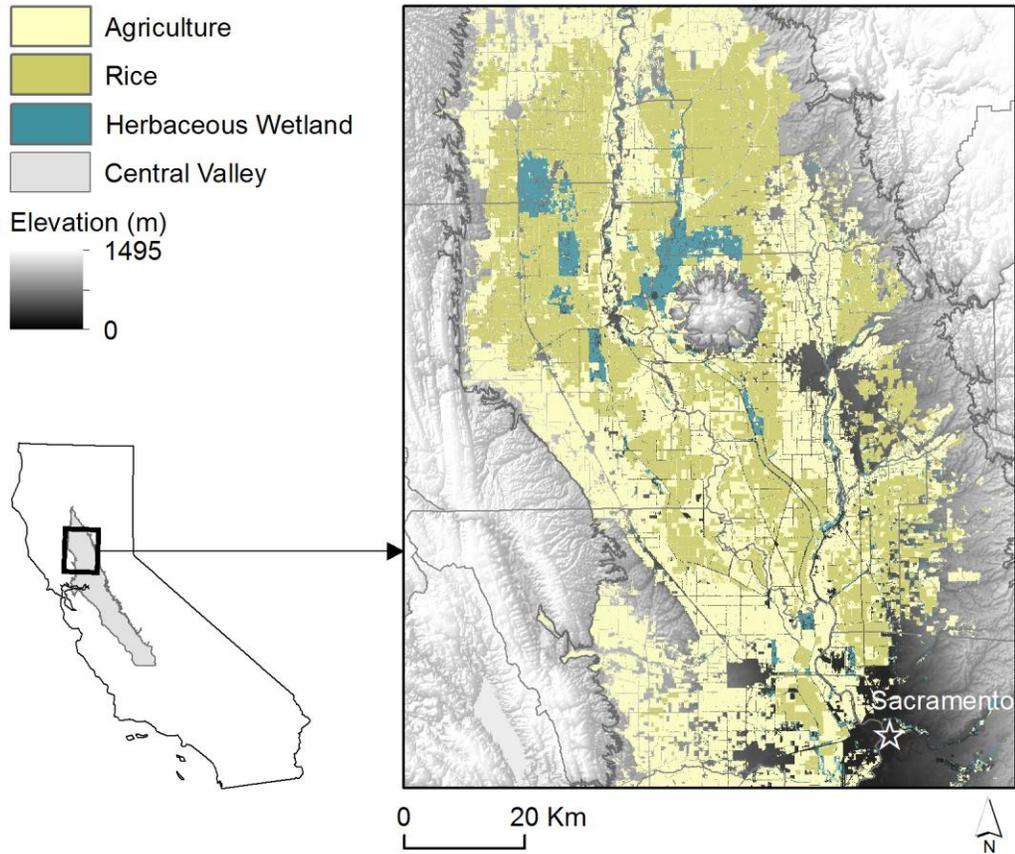
### **2.2.1 Study area**

The Sacramento Valley, in the northern Central Valley of California, is predominantly an agricultural landscape, although highly managed herbaceous

wetlands remain on federal, state, and private lands (USDA-NASS 2014; Fig. 1). More than 90% of the historically occurring wetlands have been lost in the Central Valley (Frayer et al. 1989). The Sacramento Valley hosts 96% of California's flood-irrigated rice (~20% of U.S production; Central Valley Joint Venture 2006, Strum et al. 2013), which serves as important surrogate habitat for shorebirds in areas with high wetland loss (Elphick 2000, 2010, Barbaree et al. 2015). Despite extensive historical wetland loss, the Sacramento Valley is recognized by the Western Hemisphere Shorebird Reserve Network as a site of international importance (Western Hemisphere Shorebird Reserve Network 2009). The valley provides habitat for over 400,000 shorebirds each spring, with the peak of migration typically occurring in April (Shuford et al. 1998, Central Valley Joint Venture 2006).

Much of California's water is supplied by the snowpack in the Sierra Nevada mountains, which is projected to decrease in average volume and duration in the future (Cayan 1996, Cayan et al. 2008). The Sacramento Valley receives an annual average of 890 mm of precipitation, with the majority of accumulation from late fall through early spring (NOAA National Centers for Environmental Information 2016); however this varies with climate cycles. A total of 1,488 mm of precipitation were recorded under strong El Niño conditions in 1998, while only 541 mm were recorded for 2014, the third driest year on record in the state. Local allocations and water application in the Central

Valley are driven by water rights and policy decisions, as opposed to the natural patterns of water distribution and abundance (Grantham and Viers 2014). During spring, water used in the Sacramento Valley is primarily sourced from reservoirs that capture montane snowmelt and runoff, which is delivered to wetlands and agricultural fields hundreds of kilometers away through an extensive network of canals, pump stations and levees.



**Figure 1: Land use and land cover in the Sacramento Valley, within California’s Central Valley. Herbaceous wetlands and agriculture: National Land Cover Database (Homer et al. 2015); flood-irrigated rice: (USDA-NASS 2014).**

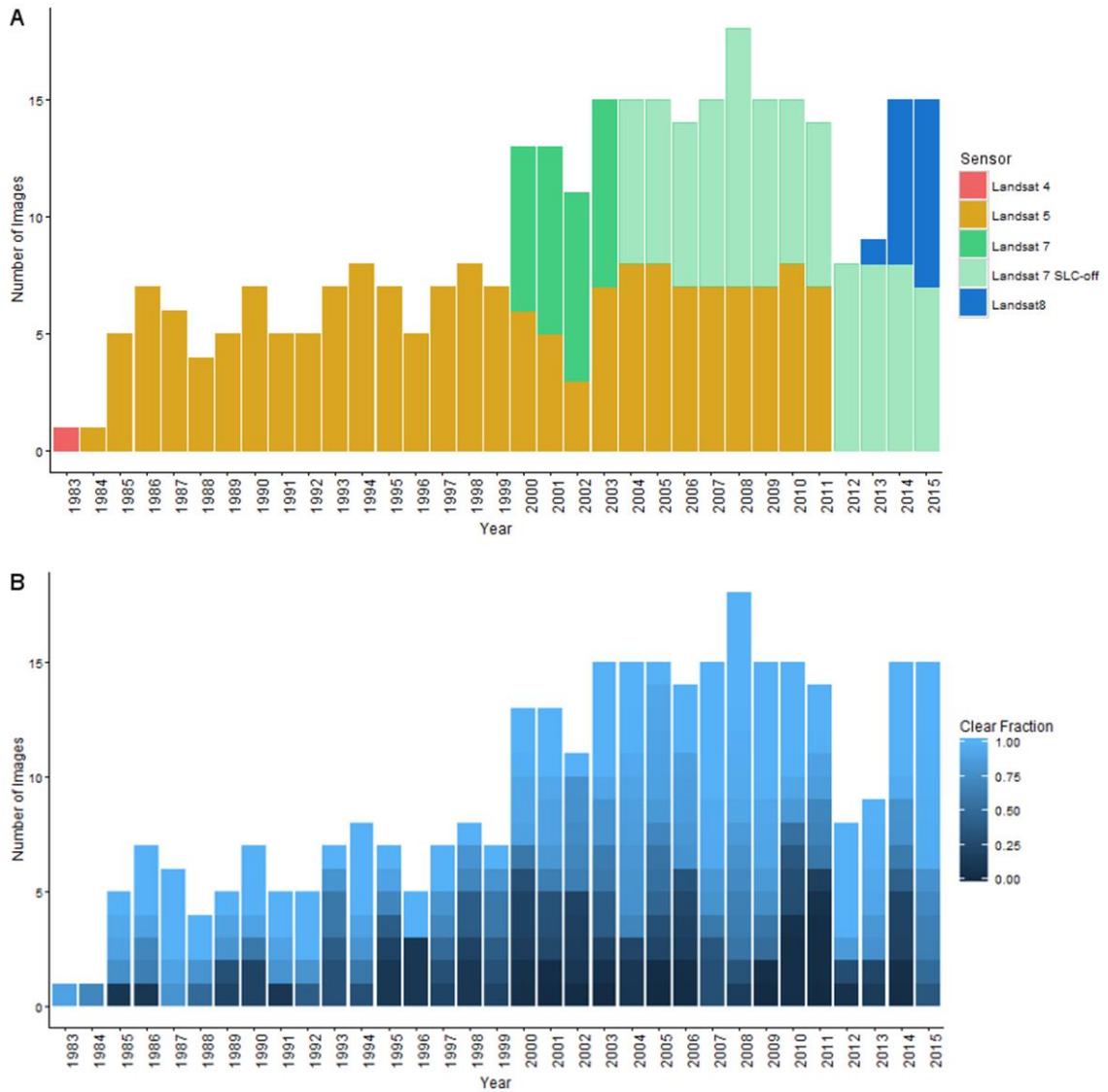
### **2.2.2 Analysis Tools**

We used the RStoolbox package in R to develop image classifications and for accuracy assessment (Leutner and Horning 2016). ArcGIS 10.3 was used to generate validation datasets, and Python was used for image processing (ESRI 2014). Modelling and statistical analysis were conducted in R using the following packages: ggplot2 (Wickham 2009), dplyr (Wickham and Francois 2015), rasterVis (Perpinan and Hijmans

2016), randomForest (Liaw and Wiener 2002), reshape2 (Wickham 2007), ROCR (Sing et al. 2005), SDMTools (VanDerWal et al. 2014), and spatial.tools (Greenberg 2014).

### **2.2.3 Landsat time series**

We gathered all available Landsat surface reflectance data for the Sacramento Valley representing the spring migration period (February – May) from 1983 – 2015 (WRS-2 path/row 44/33). Surface reflectance data were downloaded from USGS/EROS (<https://espa.cr.usgs.gov/>); these images were calibrated using the LEDAPS algorithm (Landsat 4-5, 7; Masek, J.G et al. 2013), or the L8SR algorithm (Landsat 8; Vermote et al. 2016) and CFmask (Zhu and Woodcock 2012). For the spring migration season from 1983 – 2015, we processed a total of 242 Landsat surface reflectance scenes from Landsat 4, 5, 7 and 8 (Fig. 2A). These scenes had a range of cloud cover (Fig. 2B), but only isolated portions of the study area were consistently affected (Appendix A Fig. S1).



**Figure 2: Landsat surface reflectance data availability (A) and quality (clear fraction identified by the CFmask surface reflectance product) (B) for the Sacramento Valley (WRS-2 path 44/row 33) from February to May 1983-2015.**

## **2.2.4 Comparison of methods to identify water vs. non-water**

We tested multiple methods to identify water in the study area. We used supervised maximum likelihood and random forest approaches, as well as optimized and default thresholds for commonly used water indices. To compare across both binary classifications and multi-class approaches, we generated a polygon validation dataset from a May 4, 2008 Landsat 5 image acquired under clear atmospheric conditions, using synchronous Quickbird imagery as a reference. We delineated polygons representing five land cover categories: open water, forested, other green vegetation, dry vegetation, or barren/urban, also coding each polygon as water or non-water. The open water polygons that we digitized did not include edge vegetation, but these did incorporate a mix of shallow and deep-water pixels. Training and testing points were sampled from the polygon regions using a two-stage method after Wegmann et al. (2015). First, we partitioned the polygon dataset such that approximately 70% of the polygons were used for model training and 30% for model testing, in order to maximize spatial independence. For model training, we randomly sampled 500 points drawn from each class of interest (either water/non-water or multiple land cover types) in the training polygon set, removing points drawn from duplicate cells. We assessed the final water/non-water classifications produced by each approach using independent

confirmed water and non-water locations; 250 points in each class were sampled from the May 4, 2008 Quickbird polygon testing regions and filtered to remove duplicates.

Supervised maximum likelihood and random forest (10,000 trees, mtry = 1) classifications were used to map five cover types: water (490 training points), forested (453 training points), other green vegetation (418 training points), dry vegetation (460 training points) and urban/barren (434 training points). For both supervised methods, the resulting five-class map was reclassified to produce a final map of water and non-water for comparison with binary mapping methods. All multiple-class classifications were completed using the RStoolbox package including the 30-m multi-spectral Landsat bands and the 10-m national elevation dataset (U.S. Geological Survey 2015).

We developed optimized thresholds for mid-infrared surface reflectance, the MNDWI, and the AWEInsh (non-shadow version of the AWEI) using a random forest model approach (Breiman 2001) and receiver operating characteristic (ROC) curve analysis (Fawcett 2006). A random forest model for water/non-water was built from the band or index values associated with randomly selected training points (~500 each for water and non-water). We identified an optimal threshold value using ROC analysis to determine the probability of membership in the water class that maximized the true positive rate and minimized the false positive rate (Greiner et al. 2000). The image was then reclassified using the optimized threshold to generate a water/non-water

classification. To assess the utility of threshold optimization, we also produced classifications using the default thresholds proposed for the MNDWI (Xu 2006) and the AWEInsh (Feyisa et al. 2014).

### **2.2.5 Optimized water/non-water threshold development**

We assembled ground data as close in time as possible to Landsat image acquisition dates, including high-resolution (0.46 - 2.5-m) imagery and field observations confirming water or non-water presence on the ground from January to May for multiple years (Table 1). We identified obvious water and non-water point locations from high-resolution images. Field data consisted of landscape photographs of the Sacramento Valley collected as part of a separate study (Barbaree et al. 2016); fixed-wing aircraft were used to collect these photos during clear weather at altitudes of 600-800m, with a final resolution of 75-150dpi. Reference datasets were subsequently built from these photos by manually classifying XY coordinates as water or non-water using high-resolution Google Earth imagery. We excluded reference data sources collected > 10 days before or after a low-cloud cover Landsat overpass date, leaving a total of 12 reference datasets corresponding with images from Landsat 5, 7 and 8 from 2006 to 2014 (Table 1). Due to the lack of available February reference data, we included reference data from January to represent a more comprehensive range of potential spring conditions in the study area (Table 1).

To identify a single threshold for separating water/non-water in spring, we incorporated mid-infrared surface reflectance values from confirmed water/non-water reference locations (Table 1). We conducted a 9-fold random forest model cross validation, withholding 3 of the 12 dates from each model training set to maximize

**Table 1: Surface reflectance datasets and reference data sources for confirmed water and non-water locations in the Sacramento Valley of California that were incorporated in water identification threshold optimization. DigitalGlobe data were provided by NASA's NGA Commercial Archive Data ([cad4nasa.gsfc.nasa.gov](http://cad4nasa.gsfc.nasa.gov)) under the National Geospatial-Intelligence Agency's NextView license agreement. Field data consisted of landscape photographs of the Sacramento Valley collected as part of a separate study (Barbaree et al. 2016).**

<u>Surface reflectance data</u>		<u>Reference data</u>				
Sensor	Date	Source	Date	Non-water points	Water points	Extent (km <sup>2</sup> )
Landsat 5	2006/5/30	Quickbird	2006/5/25	110	147	349.33
Landsat 5	2008/3/18	Quickbird	2008/3/24	211	153	584.45
Landsat 5	2008/5/4	Quickbird	2008/5/4	205	255	562.73
Landsat 7	2008/5/13	Quickbird	2008/5/9	149	165	1,347.66
Landsat 7	2013/1/2	field data	2013/1/7	42	159	174.64
Landsat 7	2013/4/8	WorldView2	2013/4/10	260	329	1,436.78
Landsat 7	2013/5/10	WorldView2	2013/5/18	189	242	1,131.67
Landsat 7	2014/1/5	field data	2014/1/9	199	127	104.95
Landsat 7	2014/3/10	WorldView2	2014/3/15	760	297	2,919.3
Landsat 8	2014/1/13	field data	2014/1/9	181	120	104.95
Landsat 8	2014/3/18	WorldView2, field data	2014/3/15	766	463	3,074.06
Landsat 8	2014/4/19	field data	2014/4/11	516	188	218.63
Total				3588	2645	12,009.15

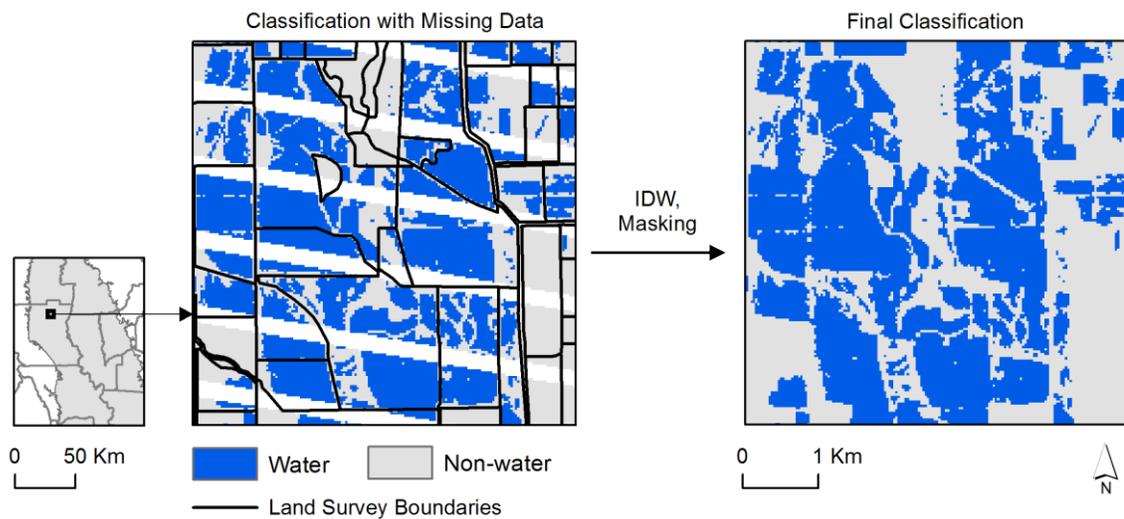
independence and rigorously assess predictive power. We identified an optimized spring water mapping threshold for the study area based on the probability of membership in the water class that maximized the true positive rate and minimized the false positive rate for the model average. To evaluate performance, we examined confusion matrices and the area under the curve (AUC) generated from cross validation of random forest model runs (Bradley 1997).

## **2.2.6 Time series image processing**

We applied the optimized spring mid-infrared threshold for classification of the entire time series for the months of February, March, April and May from 1983-2015. We limited the analysis to low-elevation, non-urban land cover unaffected by clouds and cloud shadows. Cloud and shadow-free pixels were identified using the CFmask band (Zhu and Woodcock 2012). We excluded areas mapped as 'developed' by the most recent USDA Cropland Data Layer (USDA-NASS 2014) as well as higher elevation areas of mountainous terrain outside of the current Central Valley Joint Venture planning area, which is based on topography and watersheds (Central Valley Joint Venture 2006).

Analyzing the full 1983 – 2015 time series necessitated the use of SLC-off Landsat 7 images, which are missing approximately 22% of data, even under cloud-free conditions. To address this challenge, we developed a unique interpolation approach to infer water presence in the areas of missing data. Much of the landscape has little

elevation variation and is subject to artificial flooding; therefore, we applied an inverse distance weighted (IDW) interpolation to threshold classifications, using county land use survey lines collected from 1994 to 2011 as boundaries (California Department of Water Resources 2016; Fig. 3). We also applied an IDW interpolation to the CFmask to fill cloud and shadow regions in missing data areas (Zhu and Woodcock 2012). The accuracy of the IDW interpolation was assessed for a cloud-free Landsat 7 image acquired on March 10, 2014, using a WorldView2 image collected on the same date.



**Figure 3: Example of inverse distance weighted interpolation, guided by land use survey boundaries (California Department of Water Resources 2016a) applied to classifications of SLC-off Landsat 7 imagery.**

### **2.2.7 Spatiotemporal analysis of shorebird habitat**

We analyzed long-term trends of water extent and frequency in the Sacramento Valley within the most important habitats for shorebirds: flooded agriculture and

herbaceous wetlands (Central Valley Joint Venture 2006). For each Landsat image, we calculated the proportion of water detected in the cloud-free portions of the image and estimated total water extent, in addition to water extent in each habitat type based on the most recent National Land Cover Database (Homer et al. 2015). For each two-week period in spring from 1983 - 2015, we computed mean water extent, weighting observations by the proportion of cloud-free pixels in each image. To assess long-term trends in water availability, we applied linear regression for mean water extent estimates over time within each habitat type. Within-season variability was assessed with the mean water extent and variance for each two-week period in spring; we pooled observations from all years and weighted observations by the proportion of cloud-free pixels. We also calculated water frequency for each 30-m pixel by summing the total detections of water presence, corrected for the total number of cloud-free instances.

Lastly, we explored the influence of interannual climatic variability on water extent. The California Department of Water Resources reports an annual Water Year Index for the Sacramento Valley based on the volume of total runoff in the river basin, which provides a continuous measure of climate variation (California Department of Water Resources 2016b). This index is used to classify each water year (ending in September) as 'Critical', 'Dry', 'Below Normal', 'Above Normal' or 'Wet'. We used linear

regression to assess the relationship between the Water Year Index and water extent for each two-week period from 1983-2015.

## **2.3 Results**

### **2.3.1 Comparison of methods to identify water vs. non-water**

We compared multiple methods to map water in the study area (Table 2, Appendix A Fig. S2); for the thresholds, we compared the underlying random forest models and ROC analysis results (Appendix A Table S1) in addition to the accuracy of the final threshold classifications (Table 2). Supervised classifications mapped water with high accuracy (user's and producer's accuracy > 98%; Table 2, Appendix A Fig. S2). Of the threshold methods, the optimized mid-infrared reflectance threshold achieved the highest overall accuracy (Table 2). Default thresholds for the water indices had lower user's accuracy for the water class than optimized thresholds developed for each index; the default AWEInsh threshold was the only method to have a user's accuracy <80%.

**Table 2: Assessment of multiple methods to classify open water from a May 4, 2008 Landsat image of the Sacramento Valley (path/row 44/33) using May 4, 2008 high-resolution Quickbird imagery for reference. DigitalGlobe data were provided by NASA's NGA Commercial Archive Data ([cad4nasa.gsfc.nasa.gov](http://cad4nasa.gsfc.nasa.gov)) under the National Geospatial-Intelligence Agency's NextView license.**

Accuracy	Threshold methods <sup>1,3</sup>					Supervised methods <sup>2,3</sup>	
	Optimized mid-infrared	Default MNDWI	Optimized MNDWI	Default AWEInsh	Optimized AWEInsh	Maximum likelihood	Random forest
Overall	97.33	96.69	95.04	89.88	89.90	99.38	100.00
Water producer's	100.00	99.55	90.28	100.00	98.96	98.96	98.41
Water user's	95.76	93.67	100	79.32	80.17	98.73	98.34
Non-water producer's	93.29	94.25	100	83.45	83.96	83.96	100.00
Non-water user's	100.00	99.60	90.28	100.00	99.19	100.00	100.00

<sup>1</sup> Default thresholds (value = 0) were applied to the modified normalized difference water index (MNDWI) and automated water extraction index (AWEInsh, non-shadow version). Optimized mid-infrared, MNDWI and AWEInsh thresholds were identified using random forest models trained with 481 water pixels and 492 non-water pixels; receiver operating characteristic curves were used to maximize the true positive rate and minimize the false positive rate.

<sup>2</sup> Supervised classifications were trained with randomly selected water (n=490) and non-water (453 forested, 418 other green vegetation, 460 dry vegetation, and 434 urban/barren) pixels verified from Quickbird imagery. Outputs were reclassified to water/non-water for comparison with other methods.

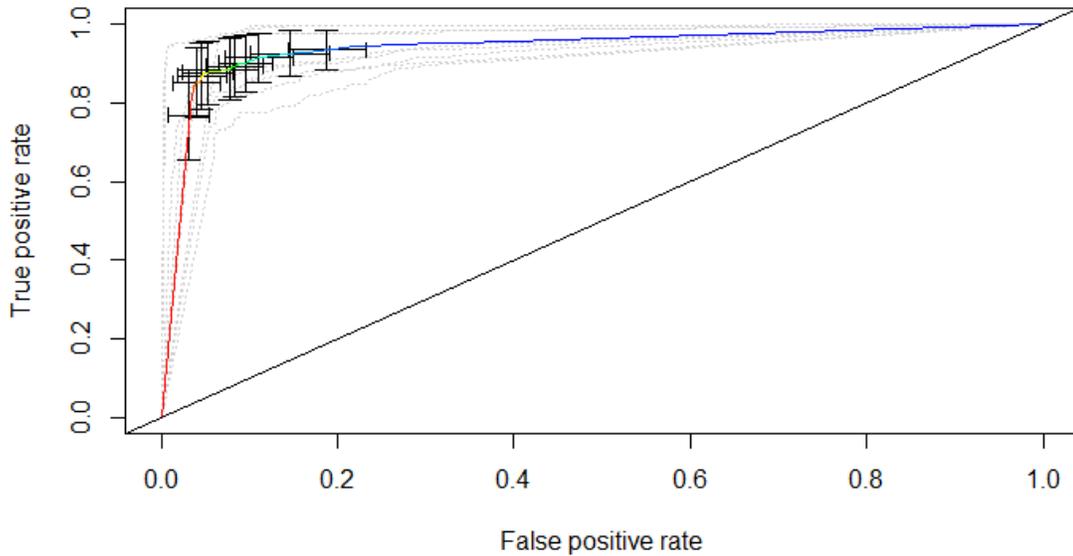
<sup>3</sup> All methods were evaluated with independent reference pixels (237 water, 247 non-water).

### **2.3.2 Evaluation of optimized spring water/non-water mid-infrared threshold**

We identified a single mid-infrared threshold to map water/non-water in spring across multiple years with nine-fold cross-validation and ROC curve analysis of water/non-water random forest models (Table 3, Fig. 4). The optimal threshold for the model average that maximized the true positive rate and minimized the false positive rate occurred at a probability of 0.76 for membership in the water class (Fig. 4). This corresponded with a mid-infrared (1.5–1.7  $\mu\text{m}$ ) surface reflectance value of 0.069, which was determined to be the optimal threshold for separating water vs. non-water across the spring image time series in the study area. Applying the spring threshold and masking steps to achieve a final classification required approximately 20 minutes per image in a parallelized R workflow on a computer with an i7 processor and 16GB of RAM.

We assessed accuracy of the optimized mid-infrared threshold classification across the time series using both estimates reported by associated random forest models and ROC curve analysis results (Table 3, Fig. 4). Random forest models use bagging to build trees with bootstrapped resampling of the training dataset, such that each tree can be tested on the out-of-bag training samples not used in building that tree (Breiman 2001). For the 9-fold cross-validation of random forest models, the average out-of-bag error rate was 9.5%, with an average of 11% error for the water class (Table 3). The non-

water class had a lower average error rate, but a higher coefficient of variation than the error rate for the water class. ROC curve analysis produced accuracy estimates and an AUC for each model. The AUC measure combines the true positive rate and the false positive rate for the full range of probabilities of membership in the water class, where values closer to 1 represent a better classifier (Bradley 1997). The average overall threshold accuracy reported by the ROC curve analysis across models was 92% and the average AUC across models was 0.94, indicating very good performance for a variety of dates and environmental conditions (Table 3, Fig. 4).



**Figure 4: Receiver operating characteristic (ROC) curves summarizing nine-fold cross validation of water/non-water random forest models used to identify a spring mid-infrared surface reflectance threshold. Dotted lines indicate ROC curves for each fold of the cross validation. The colored line is the average ROC curve; cutoffs for the probability of membership in the water class from 0 to 1 in increments of 0.1 are**

**shown with error bars indicating 95% confidence intervals for the true positive rate and false positive rate at each cutoff.**

**Table 3: Identification of a mid-infrared surface reflectance threshold to map water and non-water in the Sacramento Valley using random forest model cross-validation and receiver operating characteristic (ROC) curve analysis.**

Model run <sup>1</sup>	Random forest error estimates			ROC curve results		Threshold accuracy		
	Water	Non-water	Average out-of-bag error	AUC	Probability threshold	Water user's accuracy	Water producer's accuracy	Overall
1	.09	.08	.09	.91	.71	.87	.88	89.13
2	.12	.08	.1	.96	.81	.88	.88	95.71
3	.11	.06	.08	.9	.76	.92	.9	86.4
4	.12	.08	.1	.97	.82	.9	.91	95.43
5	.08	.05	.07	.88	.69	.92	.9	83.97
6	.1	.09	.09	.93	.74	.89	.9	89.16
7	.13	.1	.11	.98	.75	.88	.9	97.53
8	.12	.08	.09	.94	.8	.95	.92	89.95
9	.12	.11	.12	.98	.76	.89	.89	97.53
Average	.11	.08	.1	.94	.76	.9	.9	91.65
CV	12.86	18.83	14.95	3.76	5.66	2.59	1.28	5.17

<sup>1</sup>Each random forest model run incorporated water and non-water reference pixels from nine image dates, withholding data from three dates for accuracy assessment. ROC curve analysis identified the probability threshold for membership in the water class that maximized the true positive rate and minimized the false positive rate for each model run.

### **2.3.3 Effectiveness of IDW interpolation for SLC-off Landsat 7 classifications**

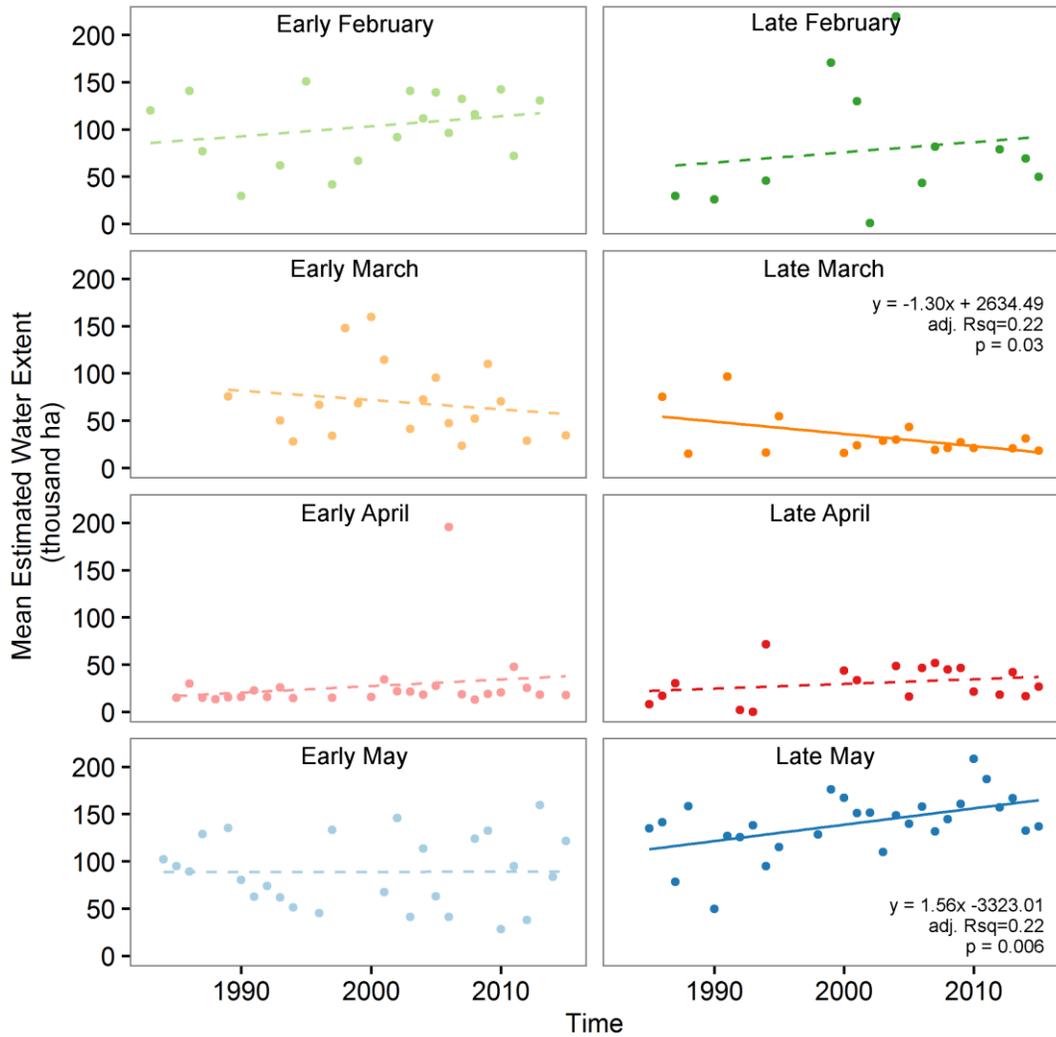
We classified water in missing data regions with high accuracy using the spring threshold and an IDW interpolation constrained by county land use survey boundaries (Fig. 3). We achieved a user's accuracy of 99% (producer's = 98%) for the March 10, 2014 Landsat 7 image with 213 water locations and 188 non-water locations verified using Worldview 2 imagery acquired on the March 15, 2014 (Table 1). Interpolation of water/non-water and the cloud and shadow mask added substantially to processing time, with up to 3.5 hours required to process SLC-off Landsat 7 images (>10 times the time needed to process other images).

### **2.3.4 Landsat-derived spring open water dynamics**

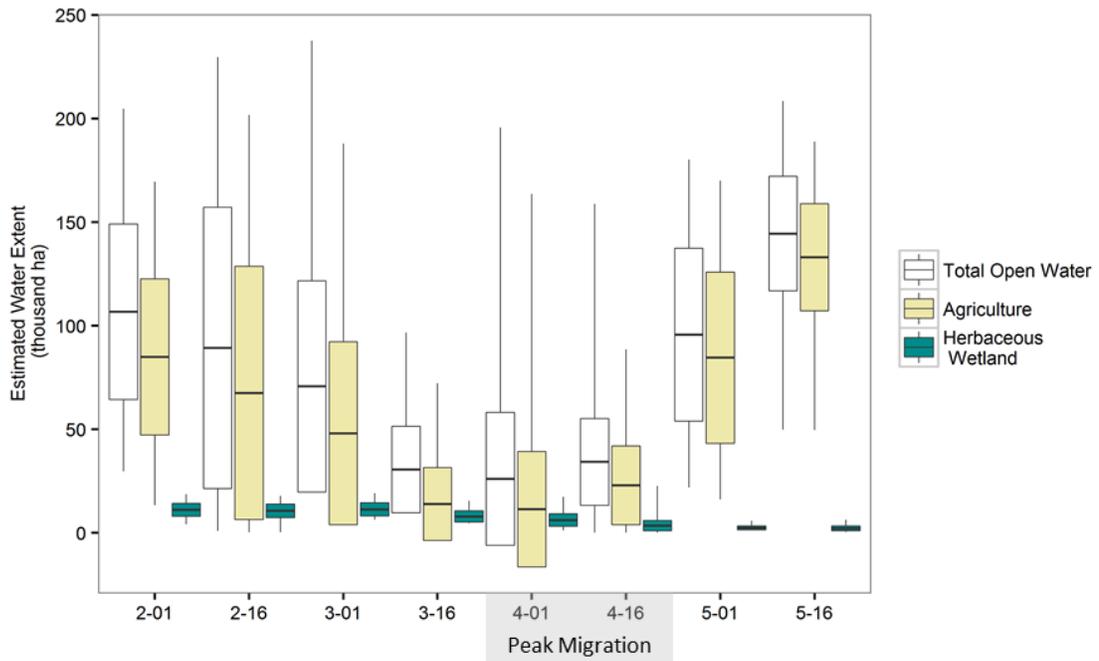
Over the study period 1983 – 2015, there was considerable variation in the estimated extent of open water in the Sacramento Valley (Fig. 5). The average water extent in the valley across the entire study period was ~75,000 ha, with a standard deviation of nearly 56,000 ha; both estimates were weighted by the cloud-free proportion of the study area for each observation. The highest confidence estimate of maximum water extent occurred on February 19th, 2004 when open water was detected on nearly 215,000 ha (27% of the study area), with a cloud-free view of 99% of the study area. Although the 2004 water year was ranked as having 'Below Normal' precipitation (California Department of Water Resources 2016b), above average precipitation occurred

that February (Daly et al. 2008). After multiple years of recent drought, a spring minimum extent of ~16,500 ha (~ 2% of the study area; 96% clear view) was observed on March 21, 2015, slightly greater than the highest confidence minimum of ~13,000 ha (<2% of the study area; 99% clear view) detected on April 11, 1988. We assessed interannual variability by conducting linear regressions of the mean estimated water extent for each 2-week period from 1983-2015 (Fig. 5). Over the study period, water extent declined by an average of 1,300 ha per year in late March (adj.  $R^2=0.22$ ,  $p=0.03$ ), and increased by an average of 1,560 ha per year in late May (adj.  $R^2 = 0.22$ ,  $p=0.006$ ).

Water extent also varied substantially within the spring season, mainly due to water management on agricultural lands (Fig. 6, Appendix A Table S2). The minimum flood extent consistently occurred in April (peak migration), due to a limited extent of flooded agriculture. In early April a weighted average of ~26,000 ha (~3% of the study area) +/-32,000 ha of open water was present in the Sacramento Valley (Fig. 6), whereas average extent increased by a factor of five by late May. Natural and managed wetlands were also subject to substantial within season variation; however herbaceous wetlands exhibited a different seasonal pattern from agricultural lands. Year to year, water extent within herbaceous wetlands consistently decreased beginning in March; the minimum herbaceous wetland water extent typically occurred in May (Fig. 6).



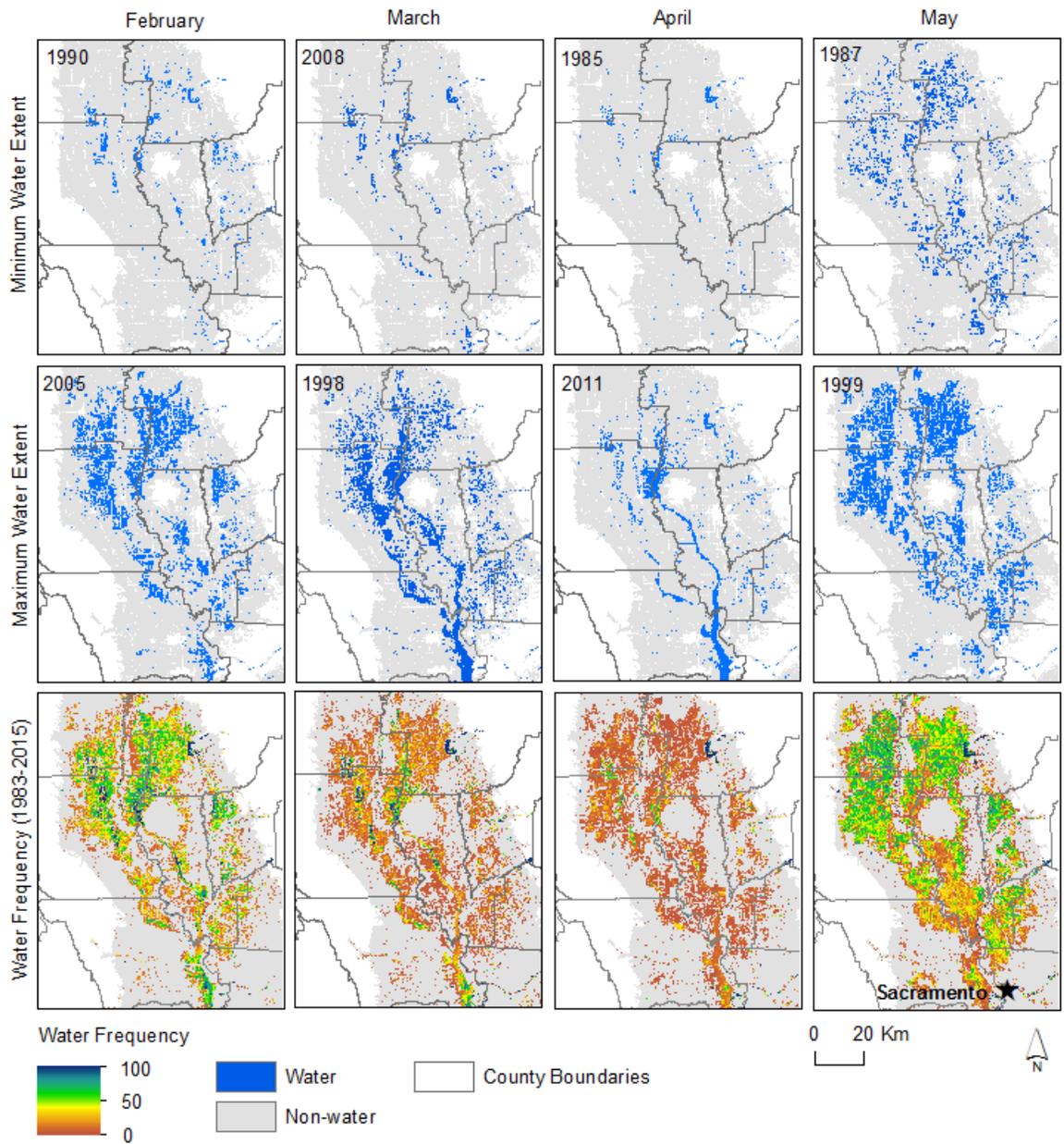
**Figure 5: Long-term spring water extent trends from 1983 – 2015 in the Sacramento Valley of California. Significant trends (linear regression,  $p < 0.05$ ) are indicated by a solid line with the equation shown, while non-significant trends are indicated by dashed lines. A significant decrease in water extent in the Sacramento Valley was observed in late March, while a significant increase in water extent was observed in late May.**



**Figure 6: Spring water extent and variability by two-week period in the Sacramento Valley from 1983 – 2015. Boxplots indicate the weighted mean extent and standard deviation of all open water in the valley, as well as water detected within agriculture and herbaceous wetlands for each two-week period in spring. The clear fraction of each Landsat image was used to weight observations.**

From 1983-2015 strong within season variation in spatial water frequency patterns across the landscape was detected from the pixel-level analysis (Fig. 7, Fig. 8), revealing striking differences between months. Similar to the pattern of water extent, the frequency of water presence across the landscape was lowest in April. Higher water frequency was observed in February and May, although the spatial patterns differed in these months. In February, high water frequency areas were more spatially

concentrated, and included riparian areas, reservoirs and herbaceous wetlands as well as agriculture. In contrast, during May a broader swath of the landscape showed



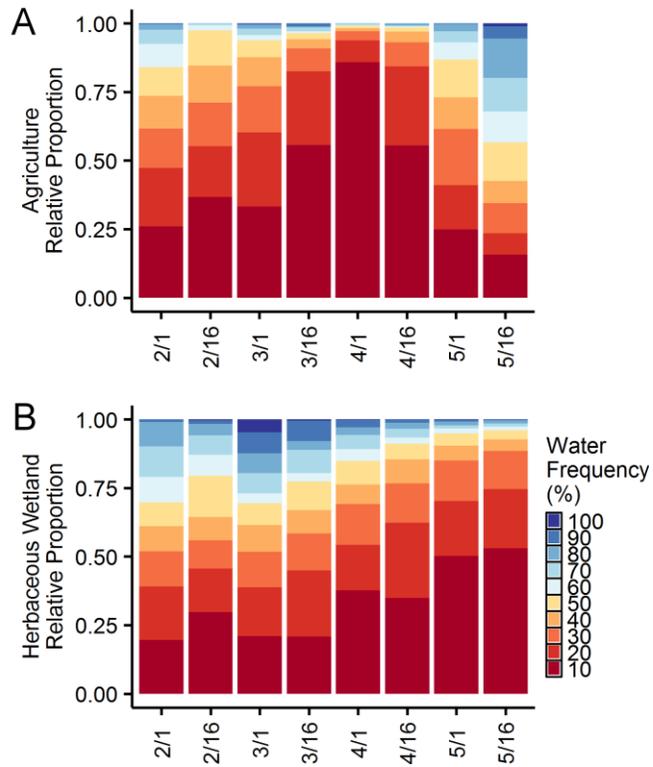
**Figure 7: Water extent and frequency for spring months in the Sacramento Valley from 1983-2015. Example minimum (top row) and maximum (middle row) water/non-water classifications for each month illustrate variability in the study area; the year of each example classification is indicated at the top left of each panel. The frequency of water detection (bottom row) was calculated as the number of times water was**

**identified in each pixel from a stack of all water/non-water classifications for each month from 1983-2015, corrected by the total number of cloud-free instances.**

moderate water frequency due to the widespread presence of active flood-irrigated agriculture operations.

Notable differences in the water frequency within each habitat type were observed from 1983-2015 (Fig. 8). During peak shorebird migration, water was detected in <10% of the cloud free views for 80% of the agricultural land in the study area, while the highest water frequency in agriculture was observed in May. Water was detected more reliably in herbaceous wetland habitat during spring, particularly on federal and state-managed lands. Herbaceous wetland water frequency was typically highest in March, becoming less reliable as the spring season progressed.

We evaluated the effect of climatic variation on water extent in each habitat type over the study period using the California Department of Water Resources' Water Year Index, which measures overall water availability in the Sacramento River Basin based on streamflow for each water year (Fig. 9). The Water Year Index was a significant, but weak, predictor of mean water extent on agricultural lands in March and April. For herbaceous wetlands, the Water Year Index was a stronger predictor of water extent, and the relationship was significant for all spring months. Results suggest that water presence in shorebird habitats is most sensitive to climate in March and April.



**Figure 8: Relativized estimates of spring water frequency within flood-irrigated agriculture (A) and herbaceous wetlands (B) in the Sacramento Valley from 1983-2015. Water/non-water classifications were combined for each two-week spring period and the per pixel frequency of water detection was calculated, corrected by the total number of cloud-free instances within each habitat type.**

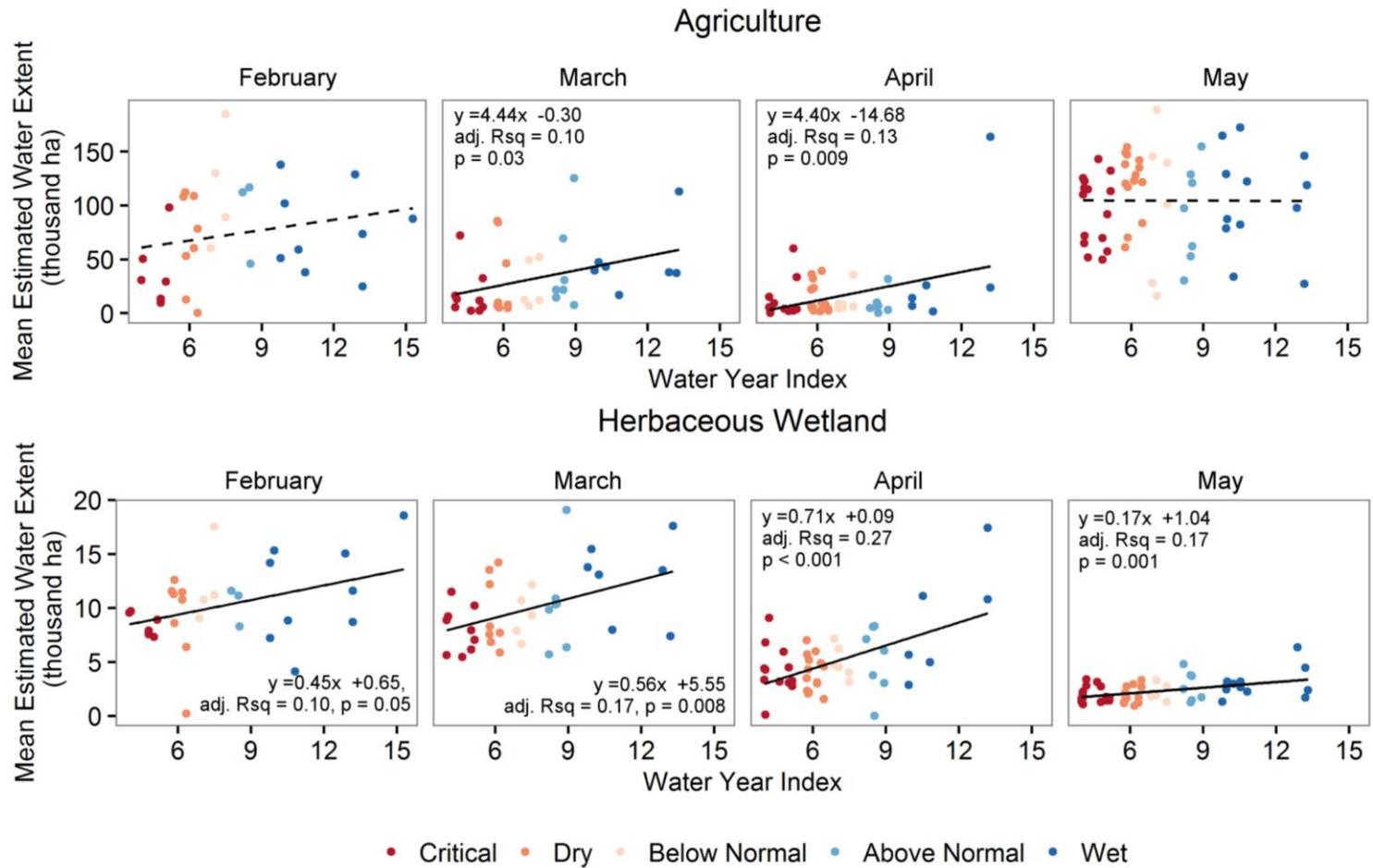


Figure 9: Annual water availability compared to spring water extent in flood-irrigated agriculture and herbaceous wetlands from 1983 – 2015. The Water Year Index for the Sacramento River Basin scales annual water availability and

designates each year as either 'Critical' ( $\leq 5.4$ ), 'Dry', 'Below Normal', 'Above Normal', or 'Wet' ( $\geq 9.2$ ) (California Department of Water Resources 2016b). Herbaceous wetland water extent was significantly correlated with the Water Year Index in all spring months; while the relationship was only significant for agricultural water extent in March and April (equations shown for  $p < 0.05$ ).

## **2.4 Discussion**

We measured water extent in the Sacramento Valley during spring for a time series spanning more than three decades. We determined that using an optimized spring mid-infrared threshold would expedite time series classification, while retaining high accuracy (Table 2, Fig. 4, Appendix A Fig. 2). We incorporated 63 SLC-off Landsat 7 images in the time series, using an interpolation technique to accurately infer the presence of water in missing data regions. Although this data processing was time intensive, it was crucial for continuity between the loss of Landsat 5 and the launch of Landsat 8, and to increase the number of cloud-free observations of the study area. For a long time series where processing of many images is necessary, the approach we used provided relatively efficient and accurate estimates of water extent (Table 2). Any supervised classification method would have required substantially more time to develop and refine training data.

This work highlights the potential for threshold methods to estimate water extent over time with high accuracy. A limited number of studies have explicitly compared different water indices (Ji et al. 2009, Campos et al. 2012, Yang et al. 2015, Fisher et al. 2016), and fewer have compared these methods against supervised classification approaches. For analysis of only a few image dates, higher accuracy could likely be achieved with supervised classification methods, but this becomes overly time intensive

for analysis of dense image stacks. The optimized threshold performed comparably to supervised classification methods that require substantial user input (Table 2, Fig. 4). However, a single global water index may not work well in all situations (Yang et al. 2015, Fisher et al. 2016). To take just one example, although the AWEI is widely recognized as having relatively low threshold variability (Feyisa et al. 2014), its success for different ecosystems was demonstrated for just five Landsat image locations. Yang et al. (2015) noted that other indices sometimes outperformed AWEI in some regions, as we found in this study (Table 2).

Only a limited number of previous studies provide methods to optimize thresholds for spectral bands and water indices to local conditions (Ji et al. 2009, Campos et al. 2012, Yang et al. 2015, Fisher et al. 2016, Sheng et al. 2016). If reference data are already available for accuracy assessment, an optimized threshold can be developed in a matter of minutes in a reproducible fashion, as we have demonstrated here with random forest models and ROC curves. Other statistical optimization techniques could also be investigated such as a recent modification of Otsu's method, which maximizes between-class variance, without biasing the threshold to the land cover category with larger within-class variance (Otsu 1979, Xu et al. 2011).

Identifying a global water identification threshold is an attractive concept; however, we suspect that optimized thresholds will be more effective at local and

regional scales, or within ecotypes. Fisher et al. (2016) developed a single threshold for a large area in Eastern Australia; however, this required hundreds of thousands of training points, which is not a practical undertaking in most cases. Furthermore, the authors did not explicitly test the accuracy of their single threshold outside of the training source areas. It makes perfect sense to use thresholds from the literature as a starting point for analysis; however, if reference data are available, we propose that researchers should tailor thresholds to their study area and period.

Tracking water trends over 32 years revealed important information about shorebird habitat dynamics in the Sacramento Valley. The finding that the minimum water extent occurs during the peak of spring shorebird migration (Fig. 6, Fig. 7) corroborates other studies (Central Valley Joint Venture 2006, Barbaree et al. 2015) and stresses the need for conservation and management actions focused on this particular window of time. The decline in March water extent that we quantified gives further credence to concern that the Sacramento Valley may not provide sufficient habitat for migrating shorebirds, particularly during drought conditions (Central Valley Joint Venture 2006). Water allocation decisions and the timing of flooding and drawdown of wetlands and agricultural fields have a strong influence on habitat and food availability; these factors therefore affect shorebird abundance and residence time in the valley. Non-linear spring water fluctuations (Fig. 5-9, Appendix A Table S2) reflect practices in flood-

irrigated rice fields, contrasting from fall migration in recent years where water extent consistently increased from September through December (Reiter et al. 2015). Managed wetlands in the Sacramento Valley provide an important source of stable habitat for shorebirds; when agricultural water reaches its spring minimum extent, managed wetlands provide a comparable amount of core open water habitat. Consistent late winter and spring water habitats, such as that provided by the National Wildlife Refuge System and State Wildlife Management Areas, are especially crucial in years when agricultural flooding is delayed, or reduced due to water allocation restrictions.

Findings have implications for wetland management under a changing climate. Water extent within both herbaceous wetlands and flood-irrigated agriculture was significantly correlated with the California Department of Water Resources' Water Year Index. While agricultural water extent was less sensitive to fluctuations in water availability, it will be affected by climate change and emerging water policy. Precipitation in the Sierra Nevada is projected to decrease, particularly the amount and duration of the winter snowpack (Cayan et al. 2008), which is the main source of surface water in warmer, drier spring and summer months. In 2015, the state water project delivered just one-fifth of the water requested by users and a zero allocation was issued by the federal water project ("Watering California's Farms" 2015). Although farmers have historically pumped groundwater to supplement limited surface water supplies,

particularly in years with low precipitation, legislation to regulate groundwater pumping recently passed in California (*Sustainable Groundwater Management Act* 2014). Restricting groundwater pumping could result in reduced flooded habitat on the landscape. Continued water deficits have heightened scrutiny of all forms of water use, and agriculture has been a popular target; rice production in 2014 was down 25% compared to the previous year, and there is increasing pressure for growers to reduce water use through drip irrigation (“Watering California’s Farms” 2015). A move away from flood irrigation over large areas could provide substantial water savings, however it would also dramatically change shorebird habitat in the Sacramento Valley and other stopovers where extensive flood irrigation is currently practiced. Such changes in water management could result in reduced yields, shifts in the types of crops cultivated, and add strain on the livelihoods of the farmers that produce food for domestic and foreign consumers.

This analysis faced some limitations. The Sacramento Valley was frequently affected by fog or cloud cover, particularly during El Niño conditions, and although Landsat’s overpass interval increased with the launch of Landsat 7, a substantial portion of available data comprised SLC-off imagery (Fig. 2). In addition to Landsat data limitations, high-resolution imagery and other reference datasets were not available for earlier years. As for observation frequency, it is possible that some agricultural fields

may transition from flooded to drained within four days (unpublished results), in contrast to Landsat's current 8-day overpass interval. This is unique to agricultural fields, as opposed to wetlands which draw down more gradually, and can affect collection of data to validate water presence and other characteristics of interest (Turpie et al. 2015). Water features may also be subject to confusion with topography and urban development; fortunately, the study area included low-elevation water features in rural areas. Estimates of water extent likely underestimated habitat availability, for example in moist soil at the field edges and in areas obscured by dense emergent vegetation. Saturated area could be estimated from the water/non-water classification products we generated by calculating the total length of water perimeters detected in the landscape.

Multiple stakeholders in California are recognizing the value of Landsat-derived water extent maps for management decisions. The technique that we used could expedite near real time mapping and monitoring efforts to inform policymakers in California, and in other regions experiencing water stress. Given access to sufficient training data, this approach could be modified and extended to meet the needs of research questions in other seasons, or other regions. The increased availability of high-resolution reference images such as the National Agricultural Imagery Program (U.S. Department of Agriculture Farm Services Agency 2016) and Google Earth offer

promising data sources that can be harnessed for threshold optimization in future studies of water dynamics.

## **2.5 Conclusions**

In this study, we mapped open water from a 32-year Landsat time series using an optimized mid-infrared reflectance threshold. Thresholds that were optimized using random forest models and ROC curve analysis produced water classifications with higher user's accuracy than classifications using thresholds from the literature. Despite the irregularity of data availability and cloud cover, we were able to gather sufficient data from Landsat's extensive record to accomplish an analysis of long-term water extent trends within important habitats for migratory shorebirds. Interpolated classifications of Landsat 7 imagery provided a valuable data source for tracking water dynamics when other cloud-free images were not available. This analysis revealed strong effects of climate and land management on the extent of water in Sacramento Valley wetlands and flood-irrigated agriculture. Water extent has been most limited at the peak of migration, when shorebirds urgently need flooded habitat for resting and foraging. Quantified reductions in March water extent also indicate that the amount of habitat leading into peak migration is dwindling. This study demonstrates the value for water and habitat management that can be drawn from analyzing an extended remotely-sensed time series. Additionally, adaptation of the reproducible threshold optimization

demonstrated here can yield efficient high accuracy classifications of water in other regions.

### **3. Quantifying shorebird habitat in managed wetlands by modeling shallow water depth dynamics**

#### ***3.1 Introduction***

Migratory shorebird populations continue to experience population declines, despite substantial effort directed at wetland conservation and restoration programs (Scottish Natural Heritage Agency 2006). Shorebirds present a unique challenge for management in that they require suitable available habitat not only within their breeding and wintering grounds, but also along their spring and fall migration corridors, which must temporally-align with migration. Shorebirds' daily energy requirements increase in preparation for spring migration (Dybala et al. 2017) and the quantity and quality of habitat available during migration can directly affect body condition, migration survival rates, and subsequent breeding season success (Brown et al. 2001). Many factors may affect the quality of available habitat for shorebirds, such as invertebrate prey density (Colwell and Landrum 1993, Farmer and Wiens 1999), vegetation type and density (Colwell 2010, Ma et al. 2010, Stutzman 2012), and the presence of predators (Zharikov et al. 2008, Stutzman 2012). However, previous work has demonstrated that habitat quantity is limited by accessibility, which is driven by a combination of water depth and bird morphology (i.e., bill and tarsus length; (Collazo et al. 2002, Strum et al. 2013).

In regions which have experienced substantial wetland loss, such as the Central Valley of California (>90% wetland loss; Central Valley Joint Venture 2006), managed wetlands and flooded agricultural fields (Taft and Elphick 2007) make up the core habitat network that shorebirds and other waterbirds rely on to rest and feed during migration, particularly under drought conditions (Schaffer-Smith et al. 2017). Wetland conservation and management in the Central Valley have historically focused on waterfowl—mainly ducks—which have very different habitat requirements from shorebirds (Safran et al. 1997, Isola et al. 2000, Taft et al. 2002, Central Valley Joint Venture 2006). In terms of habitat needs, ecologists often distinguish between diving ducks and other waterbirds, dabbling ducks, waders, and smaller shorebirds. In the Central Valley, diving waterbirds include a variety of duck species, cormorants and grebes that use water depths >25 cm, while dabbling ducks use flooded areas from 5-25 cm deep (Taft et al. 2002). Waders, such as herons and egrets, are associated with water depths of <15 cm (Taft et al. 2002). For many shorebird species, foraging is limited to water depths <10 cm deep (Safran et al. 1997, Elphick and Oring 1998, Strum et al. 2013); smaller shorebirds with short bills and short legs such as sandpipers (*Calidris sp.*) have the most narrow habitat requirements, using saturated wetland soils and regions flooded up to just 5 cm deep (Collazo et al. 2002, Taft et al. 2002, Ma et al. 2010). Shallow water areas are not only more accessible to smaller shorebirds, but facilitate higher

foraging efficiency as they recede and concentrate prey (Neckles et al. 1990, Ma et al. 2010). Direct tracking of migratory shorebirds and bioenergetics models are providing mounting evidence that there may not be sufficient shallow water habitat in the Central Valley during spring and fall migration (Barbaree et al. 2015, Dybala et al. 2017).

There is a lack of sufficient information on wetland water depth distributions over broad areas necessary to map optimal shallow water habitat accessible to both smaller and larger shorebirds during migration. Traditional static habitat mapping approaches implemented at coarse spatial and temporal scales (e.g., Guisan and Zimmermann 2000, Elith and Leathwick 2009) do not capture dynamic hydrologic changes taking place across the wetland networks that shorebirds rely on. In recent years, substantial progress has been made in tracking surface water fluctuations around the world from satellite imagery (Alsdorf et al. 2007, Pekel et al. 2016). Although the Landsat archive offers the longest satellite record with >30 years of imagery and provides a snapshot of same location at 16-day intervals under ideal cloud-free conditions, its return interval is not well matched to relatively rapid hydrologic cycles (Alsdorf et al. 2007, Turpie et al. 2015). Landsat's moderate 30-m spatial resolution also limits the ability to track dynamic water depth changes in smaller wetlands (Alsdorf et al. 2007).

Although water extent and flood duration information provides a proxy for habitat suitability for species that depend on aquatic habitats (Reiter et al. 2015, Schaffer-Smith et al. 2017), optical remote sensing data does not provide water depth information (Alsdorf et al. 2007, Turpie et al. 2015). Incorporating water depth information would offer a tremendous advance over considering all flooded areas as habitat or using expert opinion to derive water depth distributions (Dybala et al. 2017). In-situ water depth can be measured in a variety of ways, including visual monitoring of depth gauges (Strum et al. 2013), or the use of instruments such as water-level loggers or capacitance sensors (Larson and Runyan 2009). However, without topographic or bathymetric data it is not possible to estimate water depth beyond a fixed water depth monitoring location.

Accurate measurement of wetland water depth across wetlands requires knowledge of the water surface elevation as well as the topography of the underlying substrate; however, the relatively low vertical accuracy of existing digital elevation models (DEMs) and the dearth of topographic data for inland non-tidal wetland systems currently limits our ability to measure wetland water depth needed to resolve shorebird habitat suitability on the order of centimeters. A variety of approaches exist to generate digital elevation models, including using photogrammetry taking advantage of stereo-paired (Konecny 1986, Hirano et al. 2003) or multi-angle (Westoby et al. 2012) satellite imagery or aerial photos, terrestrial laser scanning (Brasington et al. 2012) or lidar

surveys (Schmugge et al. 2002, Alsdorf et al. 2007). Topographic lidar surveys use lasers with wavelengths 800 nm-1600 nm, but most often near infrared light at 1064 nm (e.g., Liu 2008), which cannot penetrate flooded areas. However, bathymetric lidar surveys using green light at 532 nm can be conducted while wetlands are flooded to map submerged topography (e.g., (Hilldale and Raff 2008). The best available global elevation dataset has a ground resolution of 30-m and an average absolute vertical accuracy of 9 m over the continental U.S. (Tachikawa et al. 2011), while the 10-m National Elevation Dataset for the U.S. has an average absolute vertical accuracy of 1.55 m (U.S. Geological Survey 2015). Unfortunately, both of these DEM products exclude waterbodies and flooded surfaces, considering them as flat regions with a single elevation value. This problem also affects DEMs that rely on topographic lidar (Alsdorf et al. 2007). For example, California's Central Valley was recently mapped with aerial topographic lidar surveys, however the derived DEM does not include wetland topography due to the presence of active flooding at the time of the surveys (California Department of Water Resources 2015).

Topographic surveys using differential GPS (Los Huertos and Smith 2013) and precise field measurements of water depth can be used to model water depth spatially at a fine-scale appropriate for tracking the presence and duration of suitable flooded habitat for shorebirds within individual wetlands. The integration of satellite-derived

water extent information with mapped bathymetry can provide additional information regarding the presence and frequency of flooding within specific water depth ranges over long time scales (Rowe et al. 2002, Munyaneza et al. 2009). Tracking water depth distributions at finer spatial and temporal resolution, and understanding the habitat patterns that result from current management practices can assist in more targeted strategies to optimize habitat across wetlands managed by state and federal fish and wildlife agencies as well as private conservation areas.

The study objectives were: 1) to model fine-scale water depth and habitat suitability at high temporal frequency using high-resolution topography, in-situ water depth measurements and satellite imagery, and 2) to assess the extent and duration of optimal shorebird habitat provided under current management practices in Sacramento National Wildlife Refuge (NWR) Complex managed wetlands, thereby helping to inform wetland restoration and water management planning efforts throughout the Sacramento Valley. Managed wetlands at Sacramento NWR Complex provide the most reliable wetland habitat within the Sacramento Valley (Schaffer-Smith et al. 2017), a globally important stopover site for migratory shorebirds during the spring migration season.

## **3.2 Methods**

We estimated water depth and optimal habitat distributions for 23 managed wetlands during spring shorebird migration using a combination of high-resolution topography surveys and water depth measurements. Secondly, we tracked optimal habitat availability during the peak of spring migration from a satellite-derived historical record of surface water extent (Schaffer-Smith et al. 2017). We used ArcGIS for processing of topography data (ESRI 2014) and R for all data analysis (R Core Team 2012).

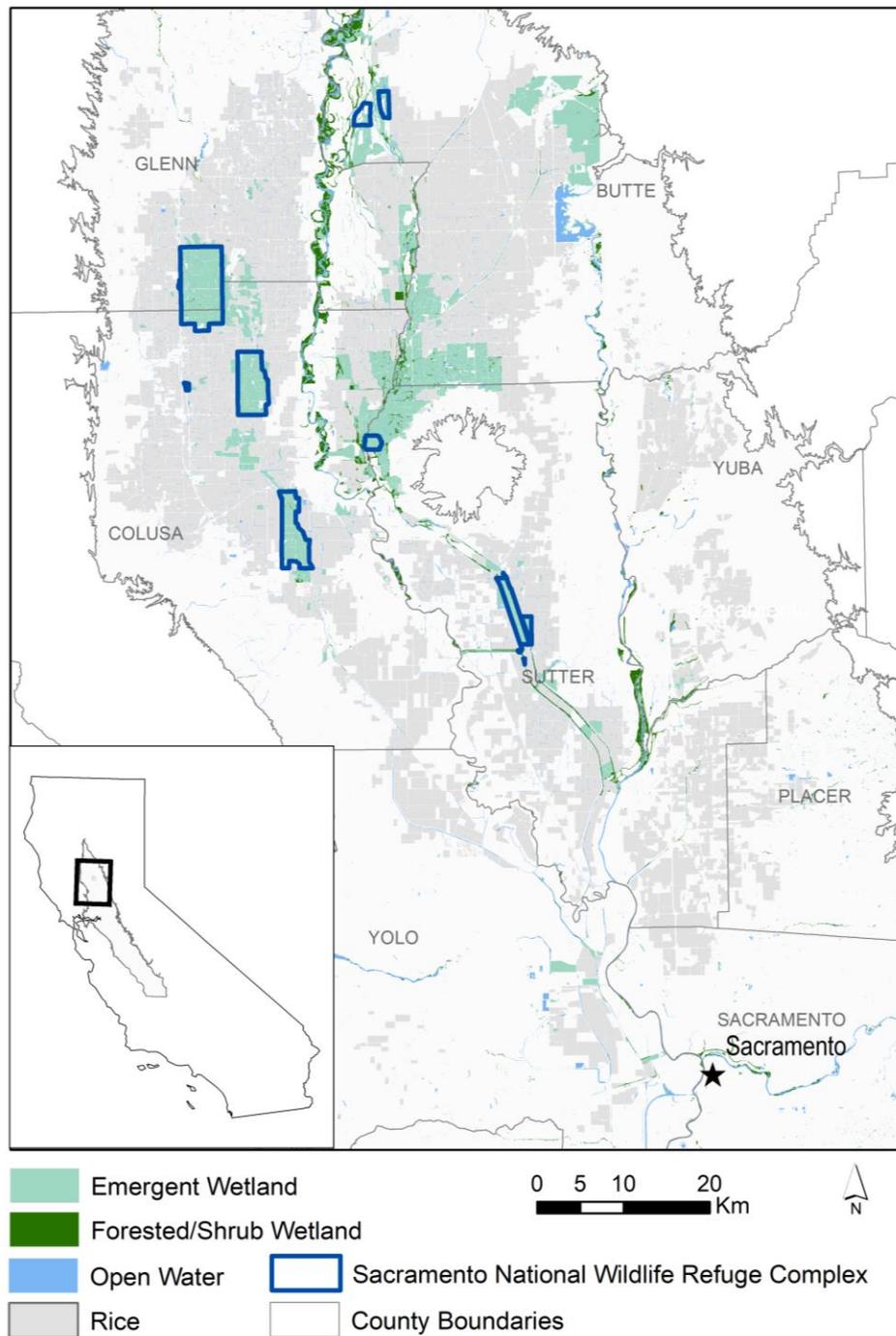
### **3.2.1 Study area**

Sacramento NWR Complex is located within the north Central Valley of California (Fig. 10), a region that supports hundreds of thousands of shorebirds during spring migration between mid-March and mid-April (Shuford et al. 1998, Central Valley Joint Venture 2006). Although 90% of Central Valley wetlands have been converted mainly to agricultural uses (Frayser et al. 1989), the rice and wetland matrix of the Sacramento Valley (northern portion of the Central Valley) is recognized by the Western Hemisphere Shorebird Reserve Network as a site of international importance (Western Hemisphere Shorebird Reserve Network 2009). A network of managed wetlands remains in the Sacramento Valley, in addition to flood-irrigated agricultural fields which support 20% of U.S. rice production (Central Valley Joint Venture 2006, Strum et al.

2013) and provide important surrogate habitat for shorebirds (Elphick 2000, 2010, Barbaree et al. 2015). Sacramento NWR Complex contains approximately 25% of the total emergent non-tidal wetland area in the Sacramento Valley mapped by the National Wetland Inventory (U.S. Fish and Wildlife Service 2016a, 2016b).

The majority of managed wetlands in the Sacramento Valley are intentionally flooded from fall through spring to support a variety of wetland dependent plant and wildlife species—this deviates somewhat from historical patterns in which wetlands were fed principally by snow melt runoff from the Sierra Nevada (Wilson and Cronon 2010). The water used in the Sacramento Valley during spring is primarily sourced from reservoirs that capture snowmelt runoff, which is then delivered to wetlands and agricultural fields hundreds of kilometers away through an extensive network of canals, pump stations and levees. Although the Sacramento Valley receives an annual average precipitation of 890 mm, mostly in late fall and winter (NOAA National Centers for Environmental Information 2017), this is highly variable depending on El Niño and other climate cycles. Under strong El Niño conditions in 1998, 1,488 mm of precipitation were recorded, while only 541 mm were recorded for 2014, the third driest year on record in the state (NOAA National Centers for Environmental Information 2017). The extent of emergent wetland water at the peak of spring migration in the Sacramento Valley can fluctuate dramatically, with a 70-80% reduction in water extent within

emergent wetlands detected during extremely dry years as compared to extremely wet years (Schaffer-Smith et al. 2017). Ultimately, water allocations in the Central Valley are highly managed and more closely tied with annual snowpack and run-off than with local precipitation.



**Figure 10: Landcover and land use in the Sacramento Valley of California. Sacramento National Wildlife Refuge Complex boundaries (U.S. Fish and Wildlife Service 2016b);**

wetland distributions (U.S. Fish and Wildlife Service 2016a), rice production areas (USDA-NASS 2014).

### **3.2.2 Site selection**

For this study, we selected 23 managed wetlands across Sacramento NWR, Delevan NWR, and Colusa NWR (Fig. 11) based on random sampling, stratified by quantiles for wetland size (small, medium, large) and historical shorebird densities (low, medium, high; based on twice-monthly surveys conducted at Sacramento NWR Complex). We included wetlands managed as seasonally-flooded marsh (which receives 70% of shorebird use at Sacramento NWR Complex), semi-permanent, and permanent ponds. Severe drought conditions were in effect when we initiated field data collection in 2015; we therefore limited site selection to those wetlands which would receive water even if the water allocation for Sacramento NWR Complex were to be cut to 40% of the normal amount. Additionally, we worked with managers to choose units without planned maintenance conflicts. Due to these limitations, it was necessary to include three semi-permanent/permanent pond sites. The 23 selected wetlands represent approximately 6% of the total area of Sacramento NWR Complex.

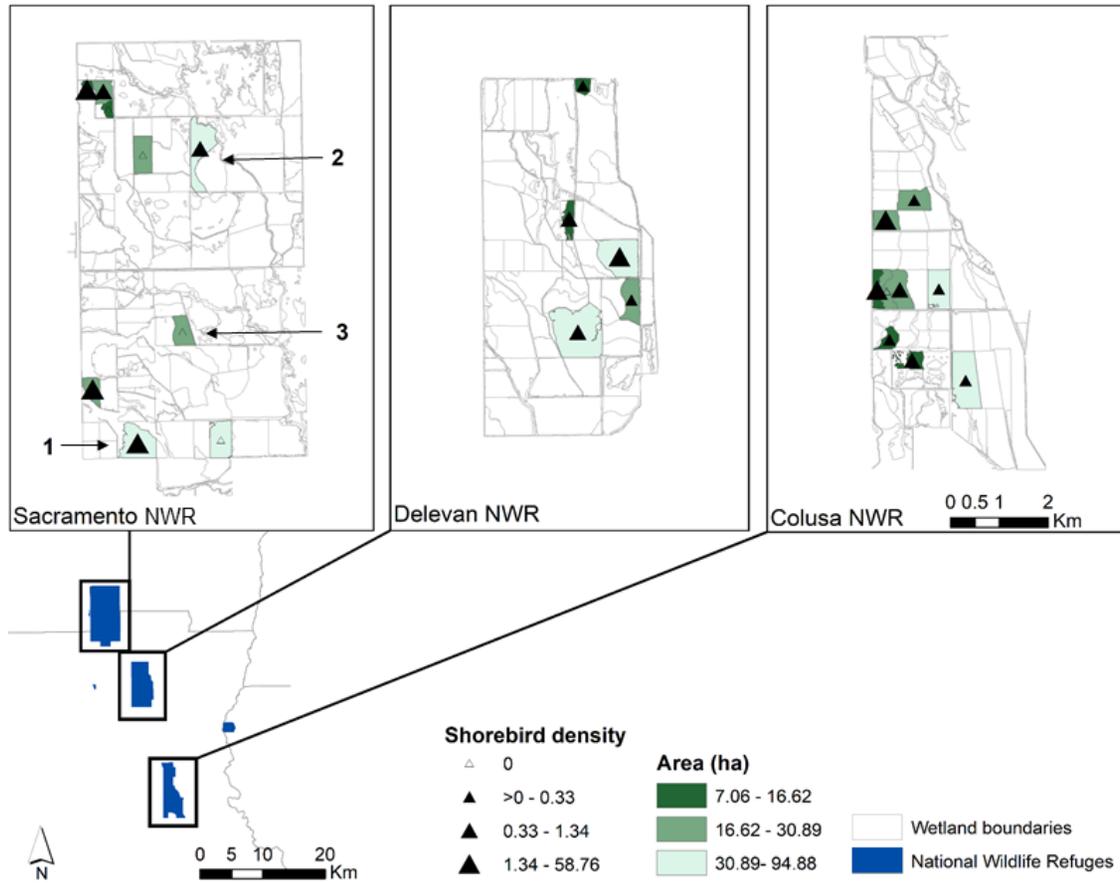


Figure 11: Monitored wetlands in Sacramento National Wildlife Refuge Complex within Sacramento, Delevan, and Colusa National Wildlife Refuges. Study sites were selected using a stratified random sample to capture the range of

shorebird densities observed from wildlife surveys (1997-2014) and a range of wetland size (U.S. Fish and Wildlife Service 2016b). Numbered Wetlands 1, 2, 3 are discussed in greater detail in Figures 3, 5, and 6.

### **3.2.3 Water depth monitoring**

Within each wetland, we deployed a 1.5 m Odyssey capacitive water depth sensor (Dataflow Systems, Ltd.). Capacitive sensors record water depth based on the linear relationship between variation in capacitance and the height variation of the water in contact with the Teflon sensor element (Larson and Runyan 2009). Each sensor was contained within a perforated 37.5mm width schedule 40 PVC shroud and mounted on a t-post at a deep point near the wetland flow outlet structure. This positioning ensured that water depth records would track changes during the wetland drawdown in mid-late spring. We recorded water depth ( $\pm 5$ mm) every 4 hours at each sensor and recalibrated each sensor periodically to ensure accurate water depth readings.

### **3.2.4 High-resolution topography mapping**

We completed a dry season real-time kinematic GPS survey for each wetland to document wetland topography at a high spatial resolution suitable for modeling water depth in centimeters. We used two Trimble AgGPS 442 units to complete surveys; the base GPS unit remained stationary at a reference location established along the wetland perimeter, while the mobile GPS unit automatically sampled elevations with a vertical accuracy of 1-3 cm along the path of an all-terrain vehicle. We surveyed each wetland with a maximum transect width of 5 m. The entirety of wetland levee perimeters were surveyed, and additional transects were covered along the slopes below levees, given

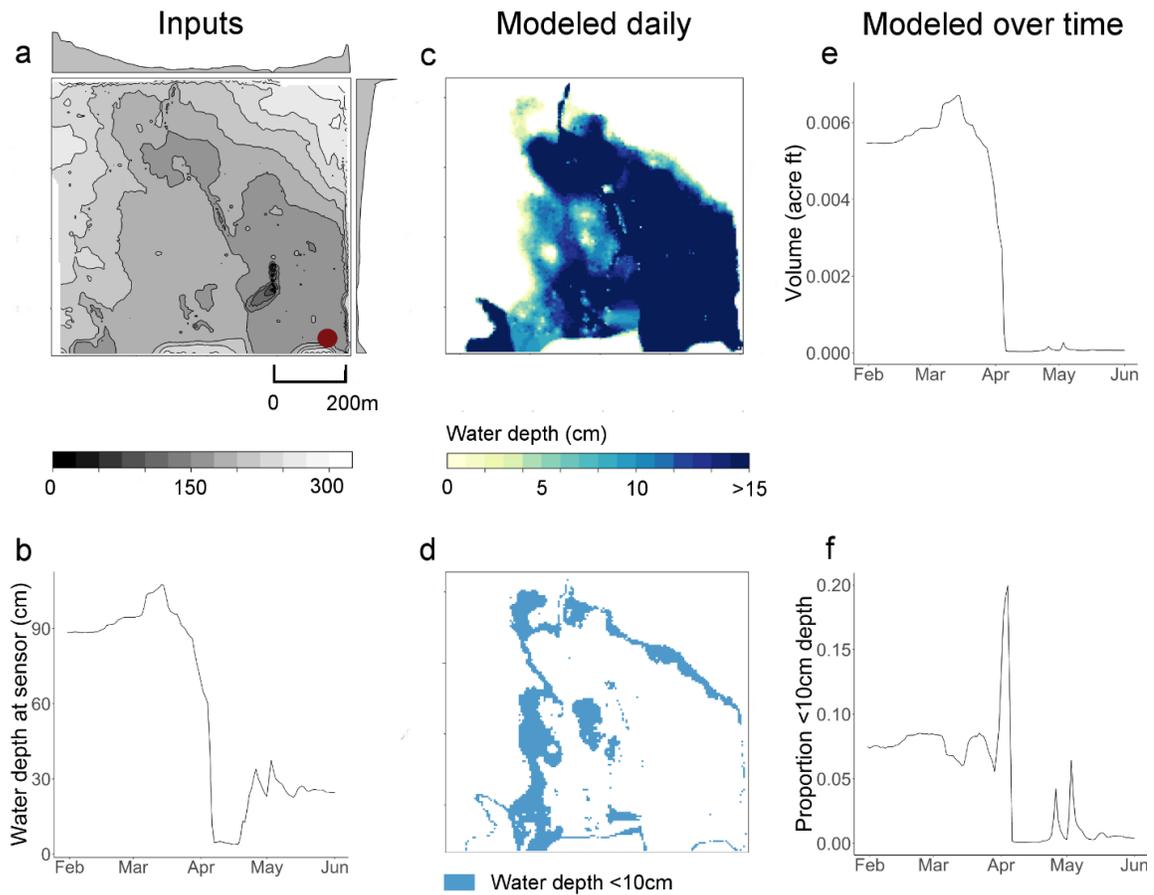
that the greatest topographic variation typically occurs at wetland edges. As needed, additional points were collected to capture notable topographic features present within wetland interiors, including islands and swales. For each wetland, we established referenced elevation points at the top and bottom of a cement water control structure, and recorded the position and base elevation of the water depth sensor.

To create digital elevation models, we first adjusted the relative elevation point clouds we collected in the field to the wetland levee boundary elevations mapped by the California Department of Water Resources' (DWR) lidar-based DEM (California Department of Water Resources 2015). Some data cleaning was required, including removal of points with poor data quality codes recorded by the GPS. We also removed potentially spurious points using DWR aerial photos collected concurrently with the DWR DEM; points which were inundated in aerial photos, yet were recorded with elevation higher than levees, were removed from the dataset. To generate a 5-m resolution DEM for each wetland, a guided inverse distance weighted interpolation was applied to the final point clouds (average point spacing = 4.16 m), constrained by wetland boundary lines (U.S. Fish and Wildlife Service 2016b).

### **3.2.5 Daily spring water depth and optimal habitat modeling**

We modeled daily water depth across each wetland and the volume of water contained in each wetland using the DEMs and water depth measurements that we

collected from February 1 through May 31, 2016 (e.g., Fig. 12). Raw water depth measurements collected at 4-hr intervals were aggregated to a daily mean water depth measurement; we assumed a uniform water surface height across the wetland based on this measurement and the known elevation at the base of the sensor. To estimate daily water depth distributions across the entirety of each wetland, we computed the difference between the water surface and the ground surface elevations from the DEM. Regions mapped up to 10 cm depth were considered to represent the extent of optimal habitat for each day. While a range of depths could be modeled for particular species and habitat types, we chose to use 10 cm given that larger shorebird species are capable of exploiting shallower water depths, while smaller shorebirds would be excluded from deeper water (Elphick and Oring 2003). For each wetland, this data processing resulted in 119 daily water surfaces, water depth maps, and maps of optimal habitat extent in spring 2016.



**Figure 12: Example of using high-resolution elevation (a), and water depth measurements (b) collected by a sensor at a fixed location (a; red dot) to infer daily spatial water depth and optimal habitat distributions (c, d; April 1, 2016 data shown), and to estimate longitudinal measures of the volume of water (f) and the proportion of optimal habitat (e) in Wetland 1 during spring 2016. Elevation isolines (a) indicate 25 cm increments and marginal histograms along the figure axes indicate average row and column values.**

### **3.2.6 Assessing potential for shallow water habitat gains through water management**

For each of the 23 wetlands, we determined the water volume that maximized the proportion of optimal habitat available for shorebirds from in-situ water depth records and DEMs (Appendix B Table S1). We calculated the increase in the proportion of optimal habitat that could be achieved by managing wetlands at these idealized volumes at the peak of migration as compared to the actual volumes detected at peak migration on April 1, 2016. To explore the influence of topography on potential habitat, we conducted a linear regression predicting maximum habitat proportion using the planimetric-to-surface area ratio (2D:3D area ratio), which is an index of topographic roughness used in habitat assessment applications (Jenness 2004). We also applied linear regression to assess the association between maximum habitat proportion and the idealized water volumes across wetlands.

To illustrate how wetland water level manipulation and topographic characteristics affect habitat suitability spatially, we simulated drawdowns for three wetlands (Wetlands 1, 2, and 3) representing a range of topographic complexity. These three wetlands were selected based on their slope variability, calculated as the difference between the maximum and minimum slope values within a 25 m moving window (Ruszkiczay-Rüdiger et al. 2009). We evaluated drawing down the relative volume of water in each wetland from 100%, down to 75%, 50% or 40% volume. We considered

100% volume to be the maximum volume captured by spring 2016 water depth data. We did not simulate volumes below 40%, as maintaining wetlands at or below this level is impractical, particularly under warm and dry conditions.

### **3.2.7 Modeling historical peak migration habitat over drought cycles using satellite imagery**

To determine the typical peak of shorebird migration, we analyzed historical bi-weekly census data collected at Sacramento NWR Complex from 1996-2015 from 382 unique survey areas. We summarized the average number of shorebirds for each spring day from February 1 through May 31st across all surveyed wetlands and all years of available spring census data. We then applied local polynomial regression fitting (LOESS; Cleveland et al. 1992) to identify the point at which migration generally peaked.

Using historical Landsat satellite imagery and mapped high-resolution wetland DEMs, we then examined water distributions and the distribution of optimal habitat within mapped wetlands at the peak of spring migration (early April) from 1996-2015. Although we had previously mapped water, non-water and cloudy (no data) regions across the Sacramento Valley during spring using all available Landsat surface reflectance imagery (Schaffer-Smith et al. 2017), we could only verify that wetland boundaries and topography had been consistent since 1996. We retained Landsat water distribution maps that represented a cloud-free view of at least 90% of the area of each

wetland based on the LEDAPS or LaSRC cloud identification algorithms (Zhu and Woodcock 2012, Vermote et al. 2016). Where multiple water extent maps were available for the period from mid-March to mid-April in the same year, we retained the map containing a higher proportion of cloud-free pixels. Each peak migration water distribution map was downscaled to match the 5-m pixels of each wetland DEM, using nearest-neighbor resampling. We then identified the highest elevation cell where water was detected for that year and generated a corresponding water surface height raster. We lastly generated a water depth map by taking the difference between the water surface height and the DEM, and used the 10-cm depth threshold to map the extent of optimal habitat at peak migration for each year.

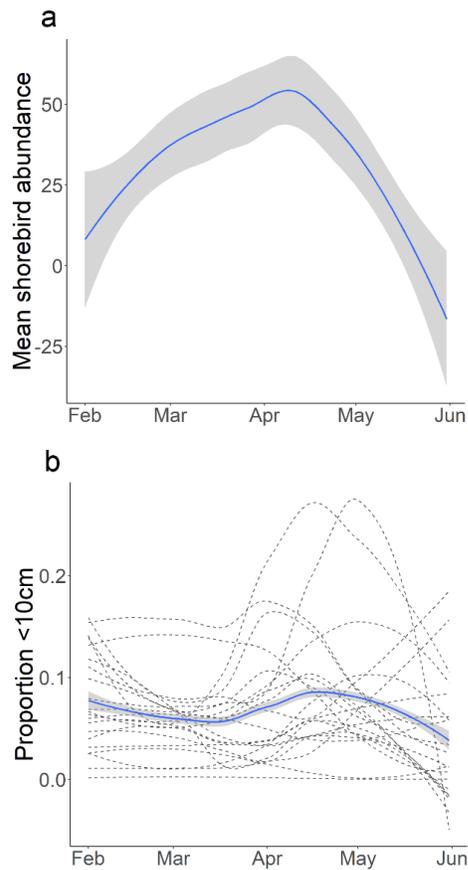
For the wetlands with historical peak migration habitat information, we examined whether the proportion of optimal habitat observed was related to water availability, reasoning that more habitat would be available in wetter years. We used linear regression to determine whether an index of water availability in the Sacramento River Region (California Department of Water Resources 2016) was a significant predictor of the proportion of optimal habitat observed over time. We also examined trends in drought vs. non-drought years using a t-test to compare the mean proportions of habitat observed across wetlands. We considered the California Department of Water Resources' designated 'Critically Dry', 'Dry', and 'Below Normal' water years to

represent drought conditions, and 'Above Normal' or 'Wet' years to represent non-drought conditions (California Department of Water Resources 2016b).

### **3.3 Results**

#### **3.3.1 Habitat suitability patterns during spring shorebird migration**

Shorebird abundance during spring in the Sacramento Valley has historically peaked in early to mid-April, yet for most of the wetlands we monitored in spring 2016, the maximum proportion of optimal shallow habitat was slightly delayed relative to bird abundance, with the peak most often occurring in mid-April (Fig. 13). Of the 23 wetlands that we monitored, 13 had only a small proportion (<10%) of flooded habitat within the optimal depth range during the peak of migration between mid-March and mid-April (Fig. 13). Only 7 wetlands provided optimal habitat within >10% of their area for a sustained period of at least 10 days, and only 2 of those provided 30 consecutive days spanning March 15 - April 15. The maximum proportion of optimal habitat observed in one wetland during spring 2016 was 50%, although this occurred in early May, after the peak of migration.



**Figure 13: Temporal mismatch between peak shorebird migration (a) and the timing of shallow water habitat availability (b) in monitored wetlands. The peak of migration (a) was estimated using historical bi-weekly shorebird census data collected at Sacramento National Wildlife Refuge Complex 1997 – 2015 (U.S. Fish and Wildlife Service 2016), averaged across all surveyed wetlands in all years. Locally weighted smoothing (LOESS) was applied to both shorebird census data and optimal habitat proportions (blue lines with standard error shown in gray). The proportions of optimal habitat in individual wetlands in spring 2016 are represented as dashed lines.**

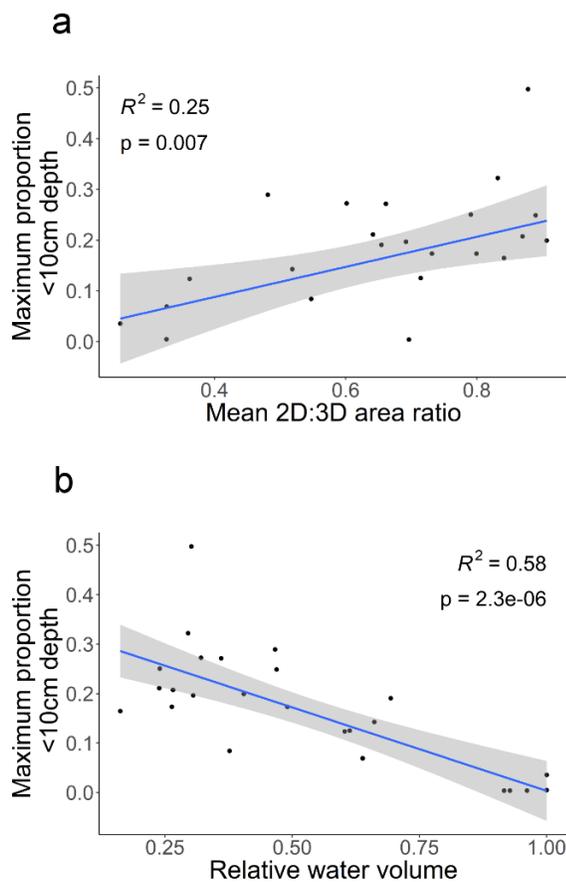
### **3.3.2 Simulated water management to maximize the proportion of optimal shorebird habitat**

We estimated that altering wetland water levels could increase the extent of optimal habitat at peak migration by 1– 1,678% (mean = 294%, median = 88%), when

compared to actual managed levels captured by water depth records on April 1, 2016 across the 23 wetlands (Appendix S1: Table S1). The wetland with the greatest potential increase in habitat extent is a large seasonally flooded marsh, with an optimal relative volume of 47%, yet was managed at 98% volume on April 1, 2016 (Appendix S1: Table S1). The water volume which optimized habitat was not consistent across the 23 wetlands, but ranged from 16% - 100% of the maximum (mean = 54%, median 48%, Appendix S1: Table S1). Two of the wetlands we monitored had optimal volumes of ~100%, but even under this optimal water management these sites each provided optimal habitat across <2% of their respective areas (Appendix S1: Table S1). For the wetlands that we measured, linear regression results indicate that those with higher mean planimetric-surface area ratios (lower topographic roughness) had more potential to provide optimal habitat (Fig. 14a;  $R^2 = 0.25$   $p = 0.007$ ). We also found that wetlands with a higher potential to provide habitat would ideally be managed with lower water volumes (Fig. 14b;  $R^2 = 0.58$   $p < 0.001$ ).

Simulated drawdowns of three representative wetlands with a range of topographic variation (Wetlands 1, 2, 3; Fig. 11; Fig. 15) demonstrated the variability of interactions between topography and water management across wetlands. Wetland 1 represented relatively low slope variability (mean =1.67, sd = 2.03), Wetland 2 represented a mid-range value (mean =4.85, sd=7.93), and Wetland 3 represented a high

value (mean =11.43, sd = 12.12). For all three wetlands, reductions in the amount of water from the maximum volume increased the proportion of optimal habitat provided (Fig. 14); Wetland 1 provided a maximum optimal habitat extent across 20% of its area at 40% volume, while Wetland 2 had a maximum optimal habitat across 12.5% of its area at 50% volume, and Wetland 3 provided a maximum optimal habitat across 27% of its area at 38% volume.



**Figure 14: Association between the maximum proportion of optimal shorebird habitat (<10 cm water depth) observed across 23 wetlands and wetland topography (a) and**

optimal water volume (b). A higher potential proportion of habitat was observed in wetlands with higher planimetric-to-surface area ratio (2D:3D area ratio; a). Idealized management conditions for wetlands with higher potential habitat proportions occurred at lower relative water volumes than for wetlands with low potential habitat proportions (b).

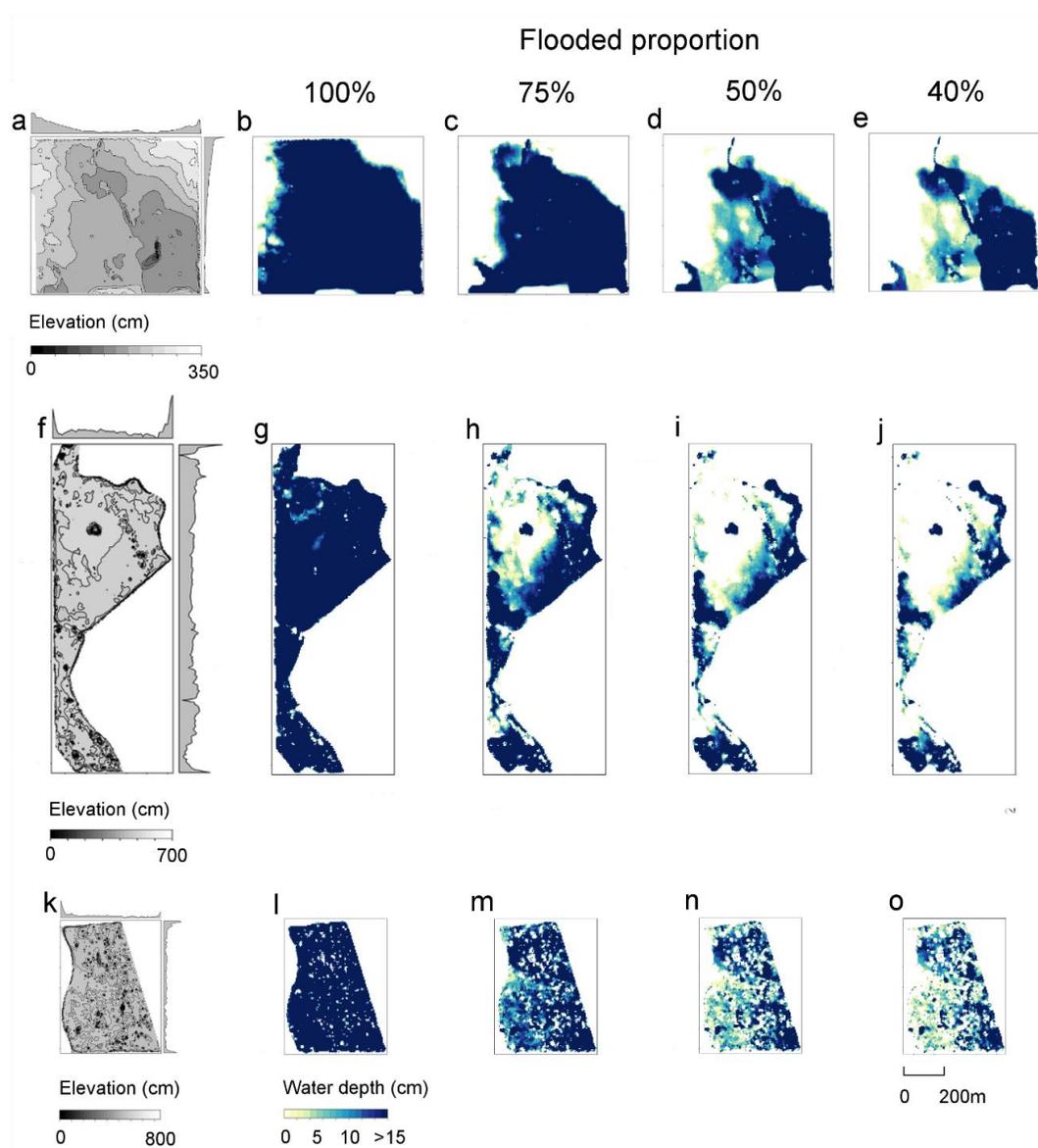


Figure 15: Implications of water level management and topographic variation for optimal shorebird habitat distributions. Wetland drawdowns were simulated for

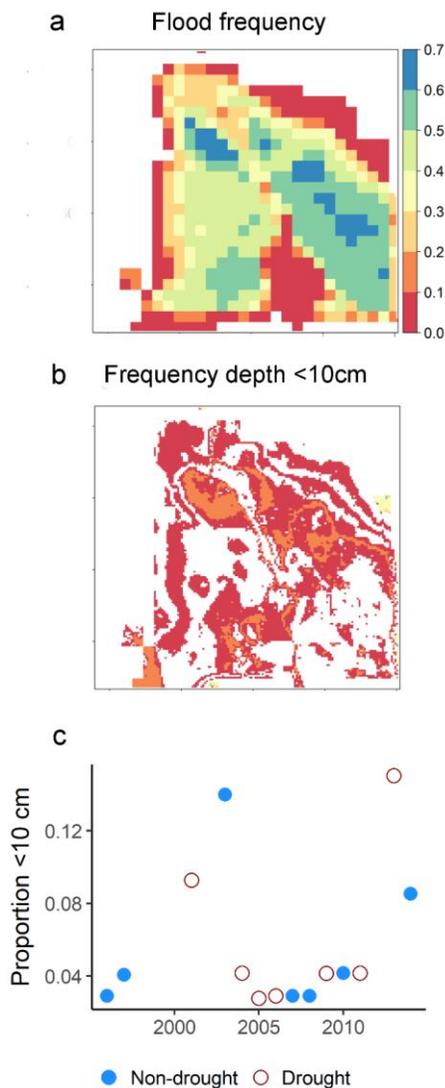
Wetlands 1, 2 and 3 (low, medium, and high mean slope variability; Fig. 11) at 100%, 75%, 50%, and 40% of the measured maximum volume. Relativized elevations for each wetland are shown in the first column (a, f, k), with isolines indicating 25 cm elevation increments and marginal histograms indicating average row and column summaries. Maximum volumes were calculated based on the maximum water depth reading at a fixed-location capacitance water depth sensor deployed in each wetland, and the difference between water surface height and the digital elevation model for each wetland (e.g., Fig. 12).

### **3.3.3 Historical peak migration habitat distributions over drought cycles**

Of the 23 wetlands that we monitored, historical peak migration water extent information from cloud-free Landsat was available for 15 locations. For those 15 wetlands, 12-14 years of water extent data were available (mean = 13.5 years). The average proportion of optimal habitat at peak migration varied from just 0.003% to 6% (mean = 1.58%) across wetlands (Appendix B Fig. S3). The frequency of optimal habitat tended to be higher in lower flood frequency portions of wetlands. For example, 51% of Wetland 1's areal extent was flooded at the peak of migration in >50% of the 14 years of available imagery (Fig. 16a); but only 18.5% of this flooded habitat could be classified as optimal habitat in >10% of years. (Fig. 16b). In contrast, the less reliably flooded zone of Wetland 1 provided optimal habitat in up to 70% of years (Fig.16b). There was no apparent association between drought and optimal habitat proportions in Wetland 1 at the peak of migration from 1996-2015 (Fig. 16c).

Across all monitored wetlands, we found no relationship between the observed proportion of optimal habitat and drought cycles over time (Appendix B Figure S3).

Relatively high and low proportions of optimal habitat occurred in both drought and non-drought years from 1996-2015 (Appendix B Figure S3). Linear regression results indicated that the index of total water availability in the Sacramento River Basin was not a significant predictor of the detected proportion of optimal habitat in wetlands ( $R^2 = 0.002$ ,  $p = 0.22$ ). A two-sample t-test also revealed no difference between the average proportion of optimal habitat provided across wetlands under drought or non-drought conditions ( $p = 0.48$ , eight drought years, seven non-drought years).



**Figure 16: Example of using satellite-based water extent mapping and high-resolution topography data to model optimal habitat distributions in Wetland 1 at the peak of spring migration (early April) from 1996-2015. Open water extent and water frequency (a) was mapped during peak migration at Wetland 1 from 1996-2015 using Landsat satellite imagery (a; Schaffer-Smith et al. 2017). We mapped optimal shorebird habitat frequencies by integrating topographic data (b; water depth <10 cm). Frequencies were computed as the proportion of times that water or habitat was detected out of the total number of cloud-free views of that pixel available over time. The proportion of Wetland 1 that provided optimal habitat from 1996-2015 was not associated with**

**drought cycles (c), based on an index of water availability in the Sacramento River Basin (California Department of Water Resources 2016b).**

### **3.4 Discussion**

We found that there appears to be even less flooded habitat in the suitable depth range for shorebirds than has been previously estimated. As part of a recent conservation evaluation for Central Valley shorebirds using bioenergetics modeling (Dybala et al. 2017) experts estimated that 75-90% of seasonal wetlands provide shallow water (<10 cm) during the month of April. However, the highest proportional coverage of optimal habitat we observed during peak migration in 2016 was 33%, lasting a duration of 8 days, while 13 of the 23 wetlands (56%) we monitored never had optimal habitat covering greater than 10% of their area. The analysis also reveals that only a small portion of surface water detected from satellite imagery is likely to be within the optimal depth range for shorebirds. Although previous research indicated that the extent of flooded habitat in the Sacramento Valley is sensitive to climate (Schaffer-Smith et al. 2017), we found no association between drought and the proportion of optimal shorebird habitat at the peak of migration from 1996-2015. This indicates the extent to which human management decisions regarding water allocations and wetland management plans can determine habitat extent, rather than annual weather variation.

The Central Valley Joint Venture Implementation Plan (Central Valley Joint Venture 2006) states that wetlands should provide 100% of shorebird energy needs from April through May, however, our results and those of Dybala et al. (2017) raise concerns that this goal may not be achievable using current management practices. Dybala et al. (2017) recommended increasing shallow water habitat (<10 cm depth) in the Central Valley by an additional 4,692 ha (11,594 ac) during mid-March through late April over the next 10 years. Given that usable habitat may have been overestimated in previous studies, there may be an even greater need for habitat, and thus there is an urgent need to prioritize shallow flooded habitat in future conservation and restoration plans.

Targeted management of wetland water levels may be a particularly important strategy to address the mismatch in the timing of migration and optimal shorebird habitat availability, and to help shorebird populations to survive future droughts. Refuges have received a guaranteed water supply since the Central Valley Project Improvement Act was enacted in 1992, but allocations are subject to reductions during 'Critically Dry' years and the water policy landscape could change in the future. Sacramento National Wildlife Refuge Complex received 75% of its full allocation in 2015, resulting in the refuge's decision to flood fewer wetlands, delay scheduled wetland flooding, reduce total inundation time (earlier drawdowns), and reduce the volume of fresh water flow-through during the inundation period. Modifying drawdown

schedules for high habitat potential wetlands to occur earlier in the spring season, and slowing or extending drawdowns, could substantially increase the proportion of optimal habitat that managed wetlands provide during peak migration. Given that idealized water volumes varied substantially across wetlands, we suggest that it is important to manage them each individually to optimize water use and habitat availability.

Practical implementation of wetland water management changes must take into account water availability, local weather, wildlife needs, vegetation management, and maintenance projects. Fortunately, most migratory waterfowl have left Sacramento NWR Complex for their breeding grounds by early April such that modifying water levels and reducing deeper water habitat would not be expected to adversely affect these populations. Although shallower water depths typically boost invertebrate productivity (Gray et al. 2013), reducing total landscape flood extent could have implications for populations of aquatic invertebrates, copepods, crayfish and other species that provide food for resident wildlife. Staggering drawdowns and managing wetlands as a mosaic with a variety of hydroperiods—as is already practiced at Sacramento NWR Complex—would help minimize adverse impacts to resident species.

There are potential conflicts between changing wetland water levels and managing vegetation. Irrigation is a key tool used by wetland managers to either promote the growth of desirable vegetation (e.g., high-yield seed plants that provide

food for wildlife) or to prevent the spread of weeds (Mensik and Reid 1995). The timing of spring wetland drawdowns is a major determinant of which plant species will germinate in seasonal wetlands (Strong et al. 1990). At Sacramento NWR Complex, early drawdowns tend to favor cool season emergents, while late drawdowns may result in poor germination and survival of important food plants for wildlife (U.S. Fish and Wildlife Service 2009). Wetland managers must consider how target species' biological requirements vary throughout the year and consider vegetation management and other logistical constraints when making water level management decisions.

Conservation objectives for shorebirds could also be achieved through other complimentary strategies. New wetland restoration projects could be designed to maximize the amount of shallow water habitat provided. Relatively flat rice fields could be also be shallowly flooded to provide significant additional habitat in lieu of restoration projects, which often involve costly earth-moving operations (Elphick and Oring 1998, Strum et al. 2013). Flooded rice fields provide abundant and accessible food resources, and may be especially attractive to shorebirds due to reduced predation risk compared to semi-natural wetland systems (Elphick and Oring 1998, Barbaree et al. 2015). Recently the highest shorebird densities recorded for agricultural land in the Sacramento Valley were documented in temporary shallow water habitat provided in rice fields through the 'Bird Returns' payment for services program (Golet et al. 2017).

Such dynamic conservation strategies (Reynolds et al. 2017) could be effective for providing supplemental habitat, so long as they do not conflict with other considerations. For example, Bird Returns fall migration contracts were limited to two week periods due to weed management and mosquito control concerns (Golet et al. 2017). Transferability of such programs to other wetland regions would depend on local conditions, including the availability and cost of water, agricultural practices and the availability of funds to incentivize private landowner participation.

The estimates of water depth, optimal habitat, and water volume described here are subject to limitations. There was some error associated with the DEMs that we generated. It was not possible to survey topography where impenetrable wetland vegetation was present (i.e., bulrush). We additionally did not survey areas where an accumulation of tall and dry vegetation was present, due to fire safety concerns. Furthermore, by using water depth to define optimal habitat we likely underestimated the actual extent of suitable areas; the analysis did not capture saturated soils which typically occur beyond the waterline, and represent important shorebird habitat. Although we only measured above-ground water volume and did not account for infiltration or evaporation processes, we do not think this affected comparison among years.

With increased availability of high-resolution DEMs, this approach could lead to better understanding of hydrologic regimes and water depth distributions at a fine spatial and temporal scale. If available, even finer resolution topography (e.g., centimeter scale) would be helpful for resolving water depth distributions across wetlands with low topographic variation. Advancements in lower-cost lidar, drone-based imagery and high-resolution satellite imagery (e.g., <4-m Planet imagery) coupled with new low-cost or open source tools for DEM generation (e.g., Pix4D, GRASS GIS, Boise Center Aerospace Laboratory [BCAL] Tools) offer exciting possibilities for expanding the global coverage of high-resolution DEM data more easily and affordably than before (Sona et al. 2014).

Once DEM data are available for wetlands, they can be combined with in-situ water depth monitoring or water extent from satellite or aerial photo imagery to track water depth over time. More frequent return high-resolution satellite imagery (e.g., near daily Planet satellite constellation imagery) is making it possible to dynamically track water extent with greater precision than ever before. In-situ depth gauges would provide a lower cost alternative to the capacitance water depth sensors used in this study (Strum et al. 2013), provided that the base elevations at gauges are known and that they are visually monitored with sufficient frequency to capture flooding and drying cycles.

To our knowledge this is the first empirical study using water depth sensor technology and high-resolution topography to track availability of suitable shallow water habitat for migratory shorebirds. Quantifying shallow water habitat more accurately with this approach may aid in better understanding the complexities of shorebird habitat selection, which depends on a suite of additional factors such as site latitude, species-specific migration timing, day length, and weather patterns (Colwell 2010). The information we have generated can also be used to guide management of existing wetlands and to inform future wetland habitat restoration projects. This approach is transferrable to other wetland systems globally, leveraged by the rapid increase in remotely sensed data in the form of bathymetric lidar surveys or multi-angular imagery collected during the dry season. Although we evaluated habitat for shorebirds using a threshold of water depths <10 cm, the determination of habitat suitability can be easily adjusted for other applications according to the requirements of the target species or group of interest.

### ***3.5 Conclusions***

Wetlands have been widely eliminated and degraded throughout the world, and many remaining wetlands are at risk. Avoiding further loss or modification of wetlands will be crucial for maintaining the important wildlife habitat and other ecosystem

services benefits that wetland ecosystems provide. Under ongoing climate change and continued human population growth, it will be ever more important to manage remaining wetlands optimally to meet multiple objectives.

For the managed wetlands that we measured in Sacramento NWR Complex, the extent of optimal shallow water shorebird habitat peaked approximately two weeks after the peak abundance of shorebirds in early April. At peak migration, the wetlands that we measured provided water depths <10 cm within less than 33% of their area, which is substantially lower than previous estimates of habitat availability in managed wetlands across the Central Valley. Although the study was limited to 23 diverse wetlands, there is some evidence that wetlands with lower topographic roughness (i.e., flatter, with more gradually sloped edges) have a higher potential to provide shallow water habitat. It may be possible to boost the amount of optimal shorebird habitat in managed wetlands by altering the drawdown schedules for high habitat potential wetlands to better coincide with the timing of peak spring migration, or to provide additional habitat during droughts.

The methods that we have illustrated in this study using high-resolution topography, in-situ water depth measurements, and satellite-based water extent maps, can be applied to more accurately track hydrologic processes in inland aquatic systems with the proliferation of available high-resolution DEMs. Topography and remote

sensing-based water depth time series could contribute greatly to vegetation community mapping and predicting the distributions of plant and wildlife species that depend on specific aquatic habitats and unique hydrologic regimes. Understanding these dynamic fine-scale hydrologic processes over broader scales can inform the acquisition of conservation properties and wetland restoration planning. As semi-arid landscapes such as the Sacramento Valley face changing precipitation regimes, data like those generated here will enable tracking of wetland water depths and volumes, highlight water use optimization opportunities, and help to justify the allocation of limited water resources.

## **4. Shorebird response to climate, water and land management at multiple scales during spring migration, Sacramento Valley of California, 1997 – 2015**

### ***4.1 Introduction***

Many shorebird species undertake long-distance journeys in the spring and fall, relying on a network of wetlands to rest and feed along the way. Over half of the 75 shorebird species in the Western Hemisphere are in decline (Brown, et al., 2001); many species face interacting threats of habitat loss and climate change (Davidson, 2014; Galbraith, DesRochers, Brown, & Reed, 2014; Morrison et al., 2006). At one extreme, climate change induced increases in drought severity are making ephemeral inland non-tidal wetlands less reliable, while projected sea-level rise would eliminate some coastal

wetlands (Galbraith et al., 2002; Werner, Johnson, & Guntenspergen, 2013). Effective conservation actions to address ongoing population declines for migratory shorebird populations require improved understanding of habitat suitability patterns over large migratory pathways, as well as knowledge of how species respond to habitat fluctuations over time. The need to understand the relevant spatial scale of habitat associations is especially true for organisms operating at different scales depending on their life history stage (e.g., breeding, dispersal and migration) (Wilbur 1980).

There are numerous factors that may drive habitat use by shorebirds during migration. It is thought that bird habitat selection proceeds in a hierarchical fashion moving from broad geographical scales informed by previous habitat selection choices of successful breeding individuals, to more fine-scale attributes, such as food availability, vegetative cover, intra- and interspecific competition, and the presence of predators (Hutto 1985, Deppe and Rotenberry 2008). Habitat configuration and proximity at a landscape scale also influence shorebird use rates (Elphick 2008, Webb et al. 2010). Inundation extent can serve as a useful broad-scale measure of habitat availability for shorebirds (Farmer and Parent 1997, Elphick 2008). Fine-scale habitat suitability is driven by factors including the presence and depth of water and the density of prey resources—typically also related to water depth and the duration of inundation (de Szalay, et al., 2003). Shorebirds typically use shallow water <15cm deep, depending

on their morphology, especially bill and leg length (Collazo et al. 2002, Taft et al. 2002), yet smaller shorebirds may only be able to access flooded areas up to five cm deep (Collazo et al. 2002, Taft et al. 2002, Ma et al. 2010). Researchers generally agree that a high density of wetland features with variable water depth will support the greatest diversity of wetland-dependent birds (Ma, et al., 2009; Taft, et al., 2002; Webb, et al., 2010). Shorebirds that select large complexes of clustered wetland habitat should be able to exploit resources more efficiently, with reduced costs of movement and search time (Albanese et al. 2012).

Until very recently, there was a lack of sufficient information regarding flooded habitat distributions over broad areas relevant for migratory shorebirds. Advancements in remote sensing have enabled tracking of relatively fine-grained hydrologic changes from satellite imagery globally (Alsdorf et al. 2007, Pekel et al. 2016), improving on static, or short-term assessments of flood extent at coarse resolution (e.g., Prigent et al. 2007, Papa et al. 2010, 25-km grid cells). This was facilitated in large part by the increase in available satellite image data, particularly the opening of the Landsat satellite imagery archive documenting 30-m resolution imagery of the globe every ~8-16 days over more than 3 decades (Wulder et al. 2012), and increased computational processing power. These developments have made possible for the first time a more dynamic

representation of changes in flooded habitat across extended wetland networks used by migratory shorebirds (e.g., Reiter et al. 2015, Pekel et al. 2016, Schaffer-Smith et al. 2017).

Fluctuations in flooded habitat can be strongly driven by seasonal and interannual climate variation. For example, the El-Niño Southern Oscillation (Feldl and Roe 2011) cyclically brings extreme wet conditions to the North American Pacific Flyway. El-Niño conditions can create additional shallow water habitat at the margins of steep-sided wetlands, but may also exclude access to invertebrate prey in low-grade wetlands that are normally traversable. In contrast, there may be dramatically reduced flooded habitat on the landscape during dry periods between El-Niño events. Substantial seasonal variation also occurs in more arid inland regions along the flyway, where wetlands tend to be more isolated and often completely dry by the end of the spring season (Central Valley Joint Venture 2006).

Spatiotemporal flooded habitat distributions are also increasingly driven by human land and water use decisions, particularly in heavily modified wetland systems in arid regions. For example, in the Central Valley of California where more than 90% of the original wetland area has been lost (Frayer et al. 1989), remaining semi-natural wetland habitat is concentrated on federal and state-owned lands and is mostly human-manipulated, rather than being driven by natural hydrologic patterns (Central Valley Joint Venture 2006). Flood-irrigated agriculture, particularly rice, also provides

important surrogate habitat for shorebirds in regions of extensive wetland loss, such as the Central Valley (Elphick 2000, 2010, Barbaree et al. 2015). The timing and type of irrigation and other land management practices can dramatically impact the amount of habitat at shorebird stopovers where flood-irrigated agriculture represents a large part of the matrix surrounding semi-natural wetlands (e.g., Schaffer-Smith et al. 2017). The extent of flooded rice dependent on marginal costs of production, federal, state and local water district allocation decisions, as well as field management by growers (e.g., earthwork, application of herbicides).

Modelling how shorebird species respond to these socio-ecological complexities necessitates a rich dataset including field observations of shorebird habitat use as well as descriptive measures of landscape-level habitat conditions, climate, and human land and water management over multiple time periods. However, integrating these diverse datasets from different sources, collected at distinct spatial and temporal scales poses challenges for using traditional species distribution (e.g., Guisan and Zimmermann 2000) and abundance modelling methods (e.g., Potts and Elith 2006). The likelihood that migrating individuals will be captured by a census is very low, resulting in extreme overdispersion, particularly for rare species. Repeated measures of both abundance data and predictors pose problems due replication in both space and time, which results in both fixed and random effects (Bolduc and Afton 2008) that also violate the assumptions

underlying most regression-based modelling methods (McCullagh and Nelder 1989, Wintle and Bardos 2006). Methods that have been proposed to account for extreme zero-inflation in species distribution (Potts and Elith 2006) and abundance modelling (Fletcher et al. 2005) do not permit assessment of multiple species, and require a regular time series that does not include missing data. While it might be advantageous to relate satellite-image derived variables representing broad-scale surface water conditions to bird census data collected for specific survey regions, both of these datasets may be subject to irregularity and missing data. Cloud cover can result in an unusable satellite image to derive predictors, and weather conditions can also affect the scheduling of bird counts used to measure the response in terms of habitat selection.

A Generalized Joint Attribute Modelling (GJAM) approach is capable of confronting the challenges of understanding migratory shorebird responses to climate and human-induced changes in habitat over time (Clark et al. 2017). A GJAM permits modeling all species jointly, providing sensitivity to all inputs and species covariance with full uncertainty. Generalized linear models (GLMs) widely used for presence and abundance modelling cannot accommodate a covariance matrix for discrete abundance data without a non-linear link function—yet the link function transforms the scale of both the covariance and the explanatory variables (Clark et al. 2017). In contrast, a GJAM maintains interpretation on the scale of observations (e.g., discrete abundance). GJAM is

also capable of handling irregular temporal data and observations with missing data— this permits inclusion of all data even when some parameters are missing (i.e., satellite-derived variables missing due to cloud cover). GJAM also specifically quantifies the relative importance of predictors for the entire community, which may result in more robust recommendations for conservation. We used a GJAM approach to address the following questions for Sacramento National Wildlife Refuge Complex (SNWRC), an internationally important non-tidal wetland shorebird stopover site along the Pacific Flyway:

- 1) What are the most important habitat characteristics that shorebirds respond to over the spring season?
- 2) How is shorebird habitat use influenced by time period within spring, the amount of flooded habitat, the type of flooded habitat, and water availability?
- 3) At what scale do shorebirds respond most to habitat fluctuations? Where should additional flooded habitat be located to augment the existing wetland habitat network?

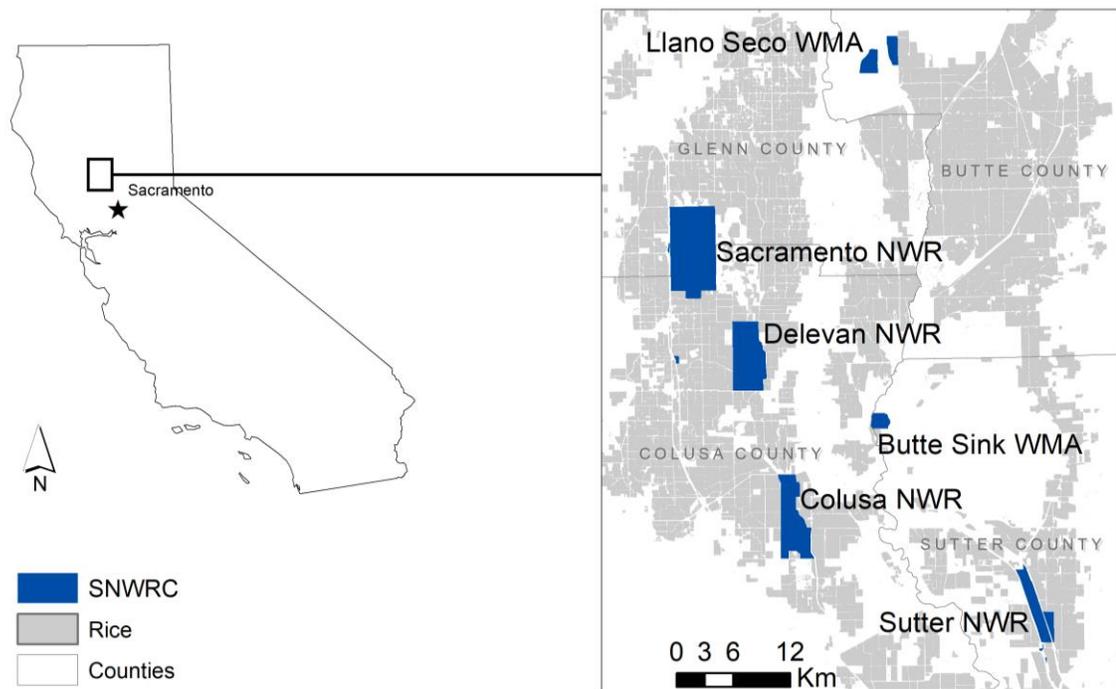
## **4.2 Methods**

To investigate the drivers of shorebird habitat use in SNWRC during spring migration we used GJAM to model discrete abundance for the community of shorebird species. We integrated census records and habitat management information documented in the field at Sacramento NWR Complex with landscape-level metrics, including remotely-sensed water extent, water and vegetation indices, as well as annual water availability and allocation data for the Sacramento Valley across almost two decades.

### **4.2.1 Study area**

SNWRC provides some of the most important semi-natural wetland habitat remaining in Sacramento Valley, in the northern Central Valley of California (Fig. 17). Although extensive historical wetland loss has occurred (Frayser et al. 1989), flood-irrigated rice also provides shorebird habitat in the surrounding matrix (Elphick 2000, 2010, Barbaree et al. 2015). SNWRC contains approximately 25% of the total emergent non-tidal wetland area in the Sacramento Valley mapped by the National Wetland Inventory (U.S. Fish and Wildlife Service 2016a, 2016c). Managed wetlands at SNWRC are intentionally flooded from fall through spring to support a variety of wetland dependent plant and wildlife species, but flooded wetland habitat can fluctuate dramatically, with a 70-80% reduction in water extent during extremely dry years as compared to extremely wet years (Schaffer-Smith et al. 2017). Most water used in

wetland and rice fields in the Sacramento Valley is sourced from reservoirs that capture snowmelt runoff, which is distributed to water districts and individual landowners through a network of canals, pump stations and levees. Ultimately water allocations in the Central Valley are highly managed and more closely tied with annual snowpack and run-off than with local precipitation.



**Figure 17:** National Wildlife Refuge (NWR) and Wildlife Management Area (WMA) study locations in Sacramento National Wildlife Refuge Complex (SNWRC), California. Extensive rice cultivation occurs in surrounding Sacramento Valley (USDA-NASS 2014).

#### 4.2.2 Shorebird census records from SNWRC wetlands

A detailed historical census record was available documenting shorebird habitat use in SNWRC wetlands. Biologists have conducted spring censuses approximately every two weeks from 1997 – 2015. Biologists drove along levee roads and visually identified birds to species and sex where possible, with the aid of a window-mounted spotting scope. Often a series of smaller impoundments are managed and surveyed together. For this study, we considered wetland units that are surveyed together as one unit of observation. Therefore, we aggregated census data up to this scale, retaining 327 wetland survey areas spread across Sacramento NWR, Delevan NWR, Colusa NWR, Sutter NWR, Llano Seco Wildlife Management Area (WMA), and Butte Sink WMA (Fig. 17). In addition to tracking the abundance of 20 distinct species (Table 4), refuge biologists recorded three mixed categories: 1) long-billed dowitcher (*Limnodromus griseus*) and short-billed dowitcher (*Limnodromus scolopaceus*), 2) least sandpiper (*Calidris minutilla*) and western sandpiper (*Calidris mauri*), and 3) a count of all ‘Other’ shorebirds that could not be identified to species. We used the ratio of separate counts of least and western sandpipers observed across Sacramento NWR Complex on a given observation date to partition mixed least and western sandpiper counts into counts for each individual species for each wetland survey area. Separate counts of long- and short-billed dowitchers were not available to facilitate the same partitioning, therefore, they

were considered as a single species in the analysis. Sanderling (*Calidris alba*) were observed extremely rarely, and we excluded this species from the analysis.

**Table 4: Shorebird species documented by the census at SNWRC.**

Common Name	Scientific Name	SNWRC species code	Linear body measurements (mm) for adults <sup>1</sup>		
			Bill	Tarsus	Body
black-bellied plover	<i>Pluvialis squatarola</i>	BBPL	29.2–32.4	43.0–46.0	280–290
semipalmated plover	<i>Charadrius semipalmatus</i>	SPPL			170–190
killdeer	<i>Charadrius vociferus</i>	KILL	18.8–23.1	32.0–38.0	200–280
black-necked stilt	<i>Himantopus mexicanus</i>	BNST	57.0–70.0	100.0–126.0	350–390
American avocet	<i>Recurvirostra americana</i>	AMAV	82.0–95.0	83.0–120.0	430–470
greater yellowlegs	<i>Tringa melanoleuca</i>	GRYE			290–330
lesser yellowlegs	<i>Tringa flavipes</i>	LEYE	30.0–39.3 <sup>1</sup>	45.5–57.8	230–250
solitary sandpiper	<i>Tringa solitaria</i>	SOSA	27.0–32.0 <sup>1</sup>	27.0–33.0	190–230
willet	<i>Tringa semipalmata</i>	WILL	58.0–65.0 <sup>1</sup>	57.0–70.0	330–410
spotted sandpiper	<i>Actitis macularius</i>	SPSA	21.0–27.0	21.0–25.0	180–200
whimbrel	<i>Numenius phaeopus</i>	WHIM	73.0–103.0	51.8–65.3	
long-billed curlew	<i>Numenius americanus</i>	LBCU	113.0–219.0	72.0–92.0	500–650
sanderling	<i>Calidris alba</i>	SAND	22.8–27.2 <sup>1</sup>	23.6–27.7	180–200
western sandpiper	<i>Calidris mauri</i>	WESA			140–170
least sandpiper	<i>Calidris minutilla</i>	LESA			130–150
dunlin	<i>Calidris alpina</i>	DUNL	31–39 <sup>1,2</sup>	26.2 ± 0.8–27.5 ± 0.8	160–220
short-billed dowitcher	<i>Limnodromus griseus</i>	DOWI	52–62.1 <sup>1</sup>	33.6–39.7	250–290
long-billed dowitcher	<i>Limnodromus scolopaceus</i>	DOWI	62.1–72.0 <sup>3</sup>	37.3–41.4 <sup>3</sup>	290 <sup>5</sup>
Wilson's phalarope	<i>Phalaropus tricolor</i>	WIPH	29.6 ± 1.1 – 33.9 ± 1.6 <sup>4</sup>	31.5 ± 1.5 – 38.5 ± 1.6 <sup>4</sup>	220–240
red-necked phalarope	<i>Phalaropus lobatus</i>	RNPH	21.5 ± 1.3 – 22.8 ± 1.2 <sup>4</sup>		180–200
common snipe	<i>Gallinago delicata</i>	COSN	58.0–72.0		280 <sup>5</sup>

<sup>1</sup>The Birds of North America Online provides a summary of linear body measurements documented in previous studies of each species, where available (Colwell and Jehl, Jr. 1994, Moskoff 1995, Skeel and Mallory 1996, Ackerman et al. 1997, Elphick and Tibbitts 1998, Mueller 1999, Robinson et al. 1999, Tibbitts and Moskoff 1999, Jackson and Jackson 2000, Rubega et al. 2000, Takekawa and Warnock 2000, Jehl, Jr. et al. 2001, Lowther et al. 2001,

Dugger and Dugger 2002, Macwhirter et al. 2002, Reed et al. 2013, Franks et al. 2014, Nebel et al. 2014, Nol and Blanken 2014, Poole et al. 2016).

<sup>2</sup>Measured as exposed culmen

<sup>3</sup>Reported as weighted means for males and females

<sup>4</sup>Reported as range of means for males and females

<sup>5</sup>Reported as mean  $\pm$  SD for males and females

<sup>6</sup>Reported as mean

### **4.2.3 Water and vegetation management at SNWRC wetland survey locations**

To describe site-specific habitat conditions, we considered flooded habitat and vegetation conditions at SNWRC wetland survey areas. During each bird census at SNWRC, biologists visually estimate the flooded area present at each wetland. SNWRC has also maintained annual management plans detailing the objectives for vegetation and water management (flood up and drawdown schedule) for each wetland since 1997. To describe the vegetative habitat conditions at each wetland survey area, we calculated the proportional coverage of different wetland vegetation types in each year.

### **4.2.4 Regional flooded habitat and vegetation conditions**

To capture regional-scale habitat conditions, we incorporated a suite of measurements derived from satellite imagery for the Sacramento Valley within 1-, 2-, 5-, 10-, and 15-km radii around each wetland survey location in the census dataset. The Landsat surface reflectance dataset provided an image of the Sacramento Valley every ~8-16 days, cloud cover permitting, for the entire span of the shorebird census record. For this study, we assumed that the Landsat image acquired closest in time to each shorebird census date represented conditions at the time of the survey. Cloud cover resulted in missing data for some observation dates for some wetlands; however cloud

cover patterns have been relatively randomly distributed across the study area (Schaffer-Smith et al. 2017) and therefore we did not expect this to substantially bias the results.

To represent regional landscape level flooded habitat composition and configuration, we calculated a range of landscape metrics (McGarigal 2006) from available satellite-based maps of open water. As part of a separate study (Schaffer-Smith et al. 2017), we previously developed an optimized threshold to map water from the mid-infrared band of Landsat, and generated maps of open water in the study area from all available Landsat surface reflectance data spanning February–May, 1984–2015. We used the spatialEco package in R (R Core Team 2012, Evans 2017) to compute metrics describing the extent, shape, clustering and connectivity of water on the landscape at multiple spatial scales surrounding each wetland survey location. To examine the influence of flooded land cover type we separately tabulated the same metrics for water detected on agriculture land and within emergent wetlands mapped by the National Landcover Dataset (Homer et al. 2015).

To describe broad-scale moisture and vegetation conditions, we also incorporated water and vegetation indices that are commonly used in regional-scale ecological studies. The modified normalized difference water index (MNDWI) (Xu 2006) is often used for detection of water and moist vegetation, while the normalized difference vegetation index (NDVI) has been widely used to measure vegetation health

and density (Pettorelli et al. 2011). Using Google Earth Engine (Gorelick et al. 2017), we generated time series MNDWI and NDVI stacks from Landsat surface reflectance data and subsequently calculated the mean and standard deviation of each index at multiple spatial scales in the vicinity of wetland survey locations.

#### **4.2.5 Regional water availability and water allocation data:**

To represent regional scale water availability, we considered the actual surface water supply and drought conditions, as well as human-managed water storage and water allocation decisions. The extent and spatial pattern of flooded habitat on the landscape in the Sacramento Valley may be limited to some extent by surface water supply, but is also strongly influenced by human water management decisions. The California Department of Water Resources' maintains an index of flow in the Sacramento River Basin as an indicator of water availability and designates each water year (October - October) as one of five different categorical types ('Critical', 'Dry', 'Below Normal', 'Above Normal' or 'Wet') based on this index (California Department of Water Resources 2016b). We further designated each year as either drought ('Critical', 'Dry', 'Below Normal') or non-drought ('Above Normal' or 'Wet') and calculated the number of years of consecutive drought conditions that had preceded each year. To explore the effect of human water management, we included records of annual water allocations to both agriculture and the refuge system (U.S. Bureau of Reclamation 2017). The volume

of water stored in Lake Shasta is another important measure that is often used in water allocation decisions—this major reservoir is located at the “headwaters” of the extensive system of canals, pumps, and ditches that distribute water throughout California (“California Data Exchange Center: Reservoirs” 2017). For each year, we retained the volume of water stored in Lake Shasta in February, because water allocations have most often been issued early in the spring season (U.S. Bureau of Reclamation 2017).

#### **4.2.6 GJAM modelling**

We filtered the complete set of >1,750 possible predictor variables to identify a subset for modelling shorebird habitat use in SNWRC (Table 5). We retained regional flooded habitat metrics which have been shown to represent complimentary aspects of landscape composition, configuration, and connectivity (Cushman et al. 2008, Wang et al. 2014). For each of these complimentary landscape metrics, we then selected the spatial scale which was most tightly associated with total shorebird species diversity at SNWRC. Furthermore, we evaluated pairwise correlations between all predictor variables, and retained those which were not collinear (Pearson’s  $r < 0.7$ ). For example, regional MNDWI statistics were unsurprisingly correlated with some of the regional-scale flooded habitat measurements, yet was a poorer predictor of shorebird diversity. We also executed preliminary models with a subset of the data to evaluate the appropriateness of parameters. Measures of variable importance, overall model fit,

variable inflation factor and inverse prediction of each parameter reported by the GJAM can be informative for variable selection (Clark et al. 2017).

**Table 5: List of predictor variables used in Generalized Joint Attribute Models of shorebird abundance by species.**

<b>Variable</b>	<b>Description</b>	<b>Spatial Scale</b>	<b>Temporal Scale</b>	<b>Ecological justification</b>
perim.m <sup>1</sup>	Wetland perimeter (m) at survey location.	Site	Twice monthly	Search area, effort
acflood <sup>1</sup>	Flooded habitat (ac) present at survey location.	Site	Twice monthly	Habitat extent
marsh <sup>2</sup>	Percent cover of seasonally flooded marsh at survey location.	Site	Annual	Vegetation
w.extent <sup>3</sup>	Extent of water detected.	Regional	Every 8-16 days	Habitat extent
w.aggregation <sup>3</sup>	Proximity of water patches detected.	Regional	Every 8-16 days	Habitat configuration
w.mean.pa.ratio <sup>3</sup>	Average perimeter-area ratio of detected water patches.	Regional	Every 8-16 days	Habitat patch shape
ndvi	Average NDVI value detected.	Regional	Every 8-16 days	Productivity, vegetation
storage <sup>4</sup>	February water storage in Lake Shasta (ac ft).	Regional	Annual	Water availability
wy.index <sup>5</sup>	Index of water supply based on Sacramento River flow.	Regional	Annual	Water availability
drought <sup>6</sup>	Presence or absence of drought.	Regional	Annual	Water availability
consec.drought <sup>7</sup>	Consecutive years of drought	Regional	Annual	Water availability
supply.refuge <sup>8</sup>	Allocation to refuges (% of requested amount).	Regional	Annual	Water availability
supply.ag <sup>8</sup>	Allocation to agriculture (% of requested amount).	Regional	Annual	Water availability
period	Jan16 = late January Feb01= early February Feb16 = late February Mar01 = early March Mar16 = late March Apr01 = early April Apr16 = late April May = May	Regional	2-week periods, except May	Migration, management

<sup>1</sup>(U.S. Fish and Wildlife Service 2016d)

<sup>2</sup>(U.S. Fish and Wildlife Service 2016c)

<sup>3</sup>Landscape water metrics and vegetation indices were computed at 1, 2, 5, 10, and 15 km from each survey area. Water metrics were computed for all open water, wetlands and agricultural lands mapped by the National Landcover Dataset (Homer et al. 2015).

<sup>4</sup>“California Data Exchange Center: Reservoirs” (2017).

<sup>5</sup>California Department of Water Resources (2016).

<sup>6</sup>Drought was determined from the California Department of Water Resources’ water year classifications (2016). Drought = 'Critical', 'Dry' and 'Below Normal' years, non-drought = 'Above Normal' and 'Wet' years.

<sup>7</sup>Consecutive years of drought were calculated as consecutive number of years of 'drought' preceding each year.

<sup>8</sup>U.S. Bureau of Reclamation (2017).

#### **4.2.7 Modelling shorebird abundance by species**

To assess how shorebird habitat use has been influenced by local and landscape habitat conditions across spring, we ran an initial GJAM (Clark et al. 2017) evaluating the discrete abundance of shorebirds observed at each survey area on each census date in response to habitat conditions at each SNWRC survey location, and in the surrounding region (Table 6, Model 1). The aggregate wetland perimeter length of each survey area was used as an effort term to account for differences in the survey time and likelihood of detection across survey locations. We expected that shorebirds would respond to both site-specific habitat conditions and landscape habitat and that the total amount of water on the landscape would be the most important regional measure of habitat. We also expected that shorebird abundance in the refuge would be higher under lower regional water extent conditions, when there would be less habitat available to choose from.

We evaluated a series of additional models to investigate whether shorebirds have responded to climate, water and land use in the study area, and to determine the most relevant spatial scale at which shorebirds have respond to habitat fluctuations (Table 3). To determine important drivers of shorebird habitat use, we assessed whether modifications to the predictor set improved the fit of the model (i.e., lower Deviance

Information Criterion [DIC]). Conceptually similar to the Aikake Information Criterion (AIC), DIC provides a way to compare Bayesian models by estimating out-of-sample-prediction error (Gelman et al. 2014). Given the dramatic fluctuations in water extent on agricultural lands in the study area during spring (Schaffer-Smith et al. 2017), we expected that shorebirds might respond to the interaction between landscape water extent and the time period within spring as well as responding to these individual factors (Table 6, Model 2). To assess the relative importance of changes in water availability due to climate, or due to human water management decisions, we examined how model fit changed with inclusion of five different indicators of water availability (Table 6, Models 3-7). To determine whether land use in flooded habitat affected shorebird habitat use, we assessed changes in model fit that resulted from substituting regional flooded habitat measurements on agricultural lands and wetlands mapped by the National Landcover Dataset in place of measurements of all open water (Table 6, Models 8-9). We expected that the total amount of all water would have a stronger effect on shorebird habitat use at SNWRC than considering which land cover types were flooded. Finally, to examine the scale at which shorebirds respond to regional water extent on the landscape—a straightforward measurement for habitat monitoring—we assessed the change in model fit from substituting different scales of measurement

(Table 6, Models 10-13). We expected that shorebirds species might respond to different scales of water extent measurements.

**Table 6: Summary of models to assess how shorebird abundance in Sacramento National Wildlife Refuge Complex responds to climate, land use, and water use at multiple scales during spring migration 1997-2015.**

*What is the relative importance of spring periods and habitat conditions in the study area?*

<u>Model run</u>	<u>Model</u>
1	Abundance, 19 spp period marsh + acflood + w.aggregation + w.mean.pa.ratio + w.extent + ndvi

*Does the interaction between spring time period and water extent matter?*

<u>Model run</u>	<u>Modifications from Model 1</u>
2	Abundance, 19 spp + w.extent*period

*Does water availability matter? Is surface water availability, drought intensity, reservoir storage, or water allocation more important?*

<u>Model run</u>	<u>Modifications from Model 1</u>
3	Abundance, 19 spp + wy.index
4	Abundance, 19 spp + drought (factor, 0 = non-drought, 1 = drought)
5	Abundance, 19 spp + consec.drought
6	Abundance, 19 spp + storage
7	Abundance, 19 spp + supply.ag

*Does the land use matter? What is the relative importance of flooding on agricultural land and flooding in emergent wetlands?*

<u>Model run</u>	<u>Modifications from Model 1</u>
------------------	-----------------------------------

8	Abundance, 19 spp	w.aggregation, w.mean.pa.ratio, and w.extent calculated only for agricultural land mapped by the National Landcover Dataset.
9	Abundance, 19 spp	w.aggregation, w.mean.pa.ratio, and w.extent calculated only for wetlands mapped by the National Landcover Dataset.

*At what spatial scale are shorebirds responding to changes in water extent on the landscape?*

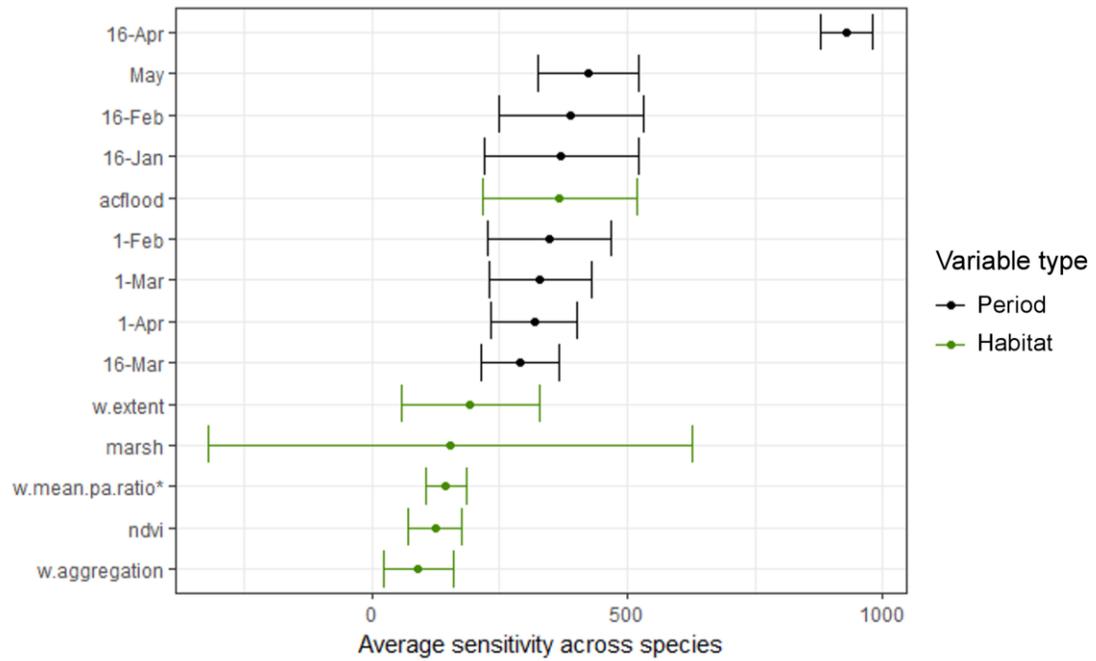
<b>Model run</b>	<b>Modifications from Model 1</b>	
10	Abundance, 19 spp	w.extent within 1 km, rather than 5 km.
11	Abundance, 19 spp	w.extent within 2 km, rather than 5 km.
12	Abundance, 19 spp	w.extent within 10 km, rather than 5 km.
13	Abundance, 19 spp	w.extent within 15 km, rather than 5 km.

## **4.3 Results**

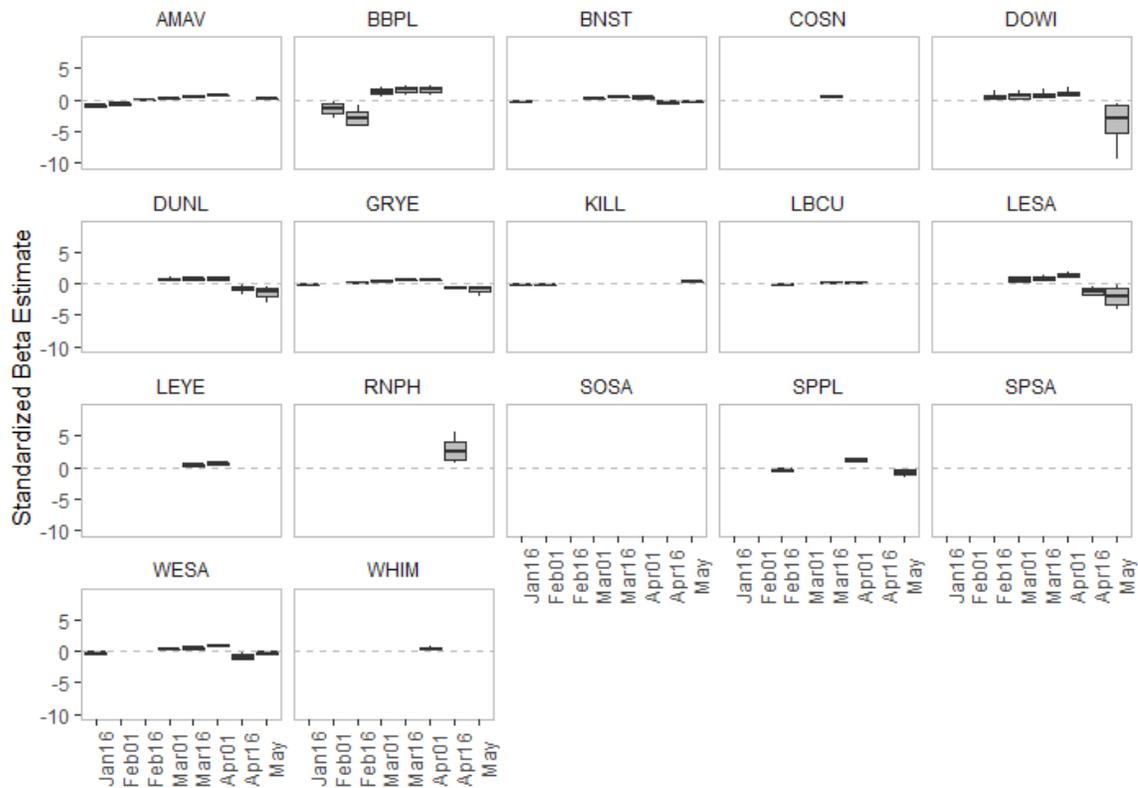
### **4.3.1 Shorebird response to local and regional habitat conditions, and time within spring**

Model 1 underpredicted shorebird abundance by species at abundances greater than 500 individuals (Appendix C: Fig. S4), and it did not predict species richness well (Appendix C: Fig. S5). Abundance across shorebird species responded more strongly to the time period than most of the habitat predictors (Fig. 18). However, the response by species varied substantially across different time periods (Fig. 19). From late January through late February, most species did not exhibit a significant response, but of those that did, most were less likely to be observed at high abundance in SNWRC wetlands. In contrast, in early March through early April, all of the species that significantly responded were more likely to be observed at high abundances in SNWRC. In late April and May, most species that responded significantly were less likely to be counted at

high abundances. Solitary sandpiper (*Tringa solitaria*, SOSA), willet (*Tringa semipalmata*, WILL), spotted sandpiper (*Actitis macularius*, SPSA), and Wilson’s phalarope (*Phalaropus tricolor*, WIPH) did not show a significant response for any spring time period.



**Figure 18: Mean and standard error of sensitivity across shorebird species to spring period (factor) and quantitative habitat predictors in Model 1.**



**Figure 19: Response by species (indicated by four letter codes; see Table 4) to spring periods in Model 1. The presence of a boxplot for each period indicates a significant response for that species to the time period. Boxplots above the dashed line at 0 indicate that a given species was more likely to be observed at high abundance during that period, while boxplots falling below the dashed line were less likely to be observed at high abundance.**

Of the habitat predictors, the extent of flooded habitat at a wetland survey location was the most important driver of abundance by species, followed by the total area of water detected from satellite imagery within five km of a survey area (Fig. 18). Of the eight species that had a significant response to flooded habitat at the survey location, six were more likely to be observed at high abundance when a larger area was flooded,

but solitary sandpiper (*Tringa solitaria*, SOSA) and spotted sandpiper (*Actitis macularius*, SPSA) were less likely to be observed under these conditions (Table 7). Six shorebird species were less likely to be observed at high abundance at SNWRC wetlands when there was more water detected on the landscape within 5km of a survey location (Table 7). The proportion of seasonally flooded marsh habitat within a survey area, the perimeter area ratio of water detected within 5 km, mean NDVI within 10 km, and the aggregation index of water detected within 10 km were of lower importance than site and landscape flood extent. Neither willet (*Tringa semipalmata*, WILL) nor Wilson's phalarope (*Phalaropus tricolor*, WIPH) responded significantly to any of the habitat predictors included in the model (Table 7).

**Table 7: Significance of response by species to predictor variables included in Model 1. Significant positive responses to a given predictor are indicated by +, while a significant negative response is indicated by -. Each species is designated by a four-letter code (see Table 4).**

Species	Spring period							Habitat					
	Feb01	Feb16	Mar01	Mar16	Apr01	Apr16	May	acflood	marsh	w.aggregation	w.mean.pa.ratio	w.extent	ndvi
BBPL		-	+	+	+			+	+	-		-	
SPPL					+				+		+		
KILL		+		+	+		+		+	+	+	-	+
BNST	+	+	+	+	+	-		+	+		-	-	-
AMAV		+	+	+	+	+	+	+	+		-	-	-
GRYE		+	+	+	+	-	-		+		+		+
LEYE					+				+				
SOSA								-					
WILL													
SPSA								-					
WHIM					+					-	+		
LBCU	-	-									+		+
WESA			+	+	+	-		+	+	+	+	-	
LESA			+	+	+				+		+	-	
DUNL		+	+	+	+	-	-	+	+		-		
DOWI		+	+	+	+	-	-	+	+		-		
WIPH													
RNPH						+							
COSN			+	+							+		

#### **4.3.2 Interactions between water extent and spring period (Model 2)**

Shorebird abundance did show a response to the interaction between the extent of water detected within 5 km of a survey area and the time period within spring, in addition to responses to these individual variables in Model 2. Including the interaction improved model fit compared to Model 1 (Appendix C: Table S4). The interaction was significant for the periods late February through late April (Appendix C: Table S5). Nine species had a significant response to the interaction, all of which were less likely to be observed in SNWRC wetlands when there was a higher extent of water on the landscape within five kilometers of a survey location.

#### **4.3.3 Effect of water availability and water allocations (Model 3-7)**

Incorporating water availability information generally improved model fit, regardless of whether climatic or human-driven measures were included (Appendix C: Table S4). The Bureau of Reclamation's water allocation to agriculture resulted in the greatest improvement in model fit, followed by water storage in Lake Shasta, drought, and California Department of Water Resources' water year index, yet including the consecutive years of drought conditions resulted in poorer model fit compared to Model 1. Only two species showed a significant response to the water year index, while six species responded significantly to water allocations for agriculture over the study period (Appendix C: Table S6).

#### **4.3.4 Effect of land use of flooded habitat (Models 8-9)**

In place of using the extent of all water on the landscape as a habitat measure, substituting water extent information for agriculture or wetland landcover types mapped by the National Landcover Dataset improved model fit compared to Model 1 (Appendix C: Table S4). Water extent on agricultural land improved the fit more than emergent wetland water extent. Shorebird species responded to different characteristics of flooded habitat on agricultural lands compared to wetlands. For flooded habitat on agricultural lands, nine species responded to the aggregation index, eight of which were more likely to be observed at high abundance in SNWRC wetlands when water on agricultural land was more aggregated (Appendix C: Table S7). For flooded habitat on wetlands, only two species responded significantly to the aggregation index. Eight species responded significantly to the shape of flooded wetland patches, with all but one of those species responding positively to a higher average perimeter area ratio. Nine species also responded significantly to the total extent of water detected in wetlands.

#### **4.3.5 Scale of shorebird response to landscape water extent (Models 10-13)**

The scale at which water extent on the landscape was measured did affect the fit of models of shorebird abundance by species. The best model fit was produced when using landscape water extent calculated within 2 km of a wetland survey location, followed by 10km, and then 5km scale used in Model 1 (Appendix C: Table S4). Water

extent calculated at 1 km and 15 km scales resulted in poorer fit compared to that of Model 1. At least four shorebird species responded significantly to each scale at which water extent was measured around survey locations (Appendix C: Table S8). Although most species that responded significantly had a negative response to greater water extent near survey locations, American avocet (*Recurvirostra americana*) and dunlin (*Calidris alpina*) both responded positively to water extent measured within one kilometer of survey locations.

#### **4.4 Discussion**

This study has provided a novel assessment of shorebird habitat use drivers over nearly two decades at SNWRC in response to flooded habitat fluctuations, water availability, and land use. Higher abundances at SNWRC in late March and early April are probably due in large part to the timing of spring migration for which populations have evolved in response to resource conditions over long timescales. However, increased abundances at SNWRC could also be an indication of crowding in response to a characteristic seasonal scarcity of flooded habitat in the Sacramento Valley. If there is insufficient habitat to support shorebird energy requirements during spring migration, impacts could include increased competition, lower foraging success, reduced stay duration, and reduced success in the subsequent breeding season (Baker et al. 2004, Finch et al. 2014), or direct mortality due to starvation (Colwell 2010).

Findings also have implications for wetland management under drought conditions. According to the model, only some shorebird species were sensitive to drought. This may be because SNWRC has received a guaranteed supply of water since 1992 under the Central Valley Project Improvement Act, making the wetlands where shorebirds were observed in the census relatively resilient to droughts over the study period. However, allocations to the refuge can be reduced in 'Critical' water years, as occurred in both 2015 and 2016, and such policies are subject to change. A recent study projected that there will be an 85% decline in the Sierra Nevada snowpack by 2100 under a 'business-as-usual' emissions scenario (Berg and Hall 2017), which would dramatically reduce the primary water source for the Sacramento Valley. According to model results, shorebird abundance at SNWRC responded more to human-manipulated water availability (i.e., water allocation to agriculture, volume of water stored in Lake Shasta) than indicators based on instream flow that are less subject to human modification. Under reduced water supply conditions, human water management decisions may be even more influential in shaping the flooded habitat networks used by shorebirds.

Land use and water use changes are likely to be entangled with climatic changes in determining future shorebird habitat extent in the Sacramento Valley. In this analysis, we found that water extent on agricultural lands was more influential than considering

water detected in emergent wetlands, or all water on the landscape. This is unsurprising given that rice represents the largest potential habitat area for shorebirds in the region (Central Valley Joint Venture 2006), while measurements of all open water include riverine areas and reservoirs that do not provide significant shorebird habitat. Based on model results, we would expect that reducing the area of active rice cultivation or reducing the use of flood-irrigation could exacerbate the existing seasonal habitat scarcity and increase crowding at SNWRC. The extent of flooded habitat in the Sacramento Valley has typically decreased in March and April due to agricultural practices, which can include drying, and re-leveling fields before reflooding them for the upcoming growing season late April or early May (Schaffer-Smith et al. 2017). During spring, the amount of rice grown and the timing of field draining, field preparation, seeding and reflooding depends on marginal costs of production, weather, and water allocations, among other considerations. Drought and delayed water allocations in the spring seasons of 2015 and 2016 resulted in high uncertainty for farmers, and limited flooded habitat available in agricultural fields during shorebird migration. There is also increasing pressure on rice growers to increase water use efficiency (e.g., “Watering California’s Farms” 2015), which could reduce the amount of flood-irrigated agriculture in the landscape in the future.

There was some uncertainty in model predictions of abundance by species. This could be due in part to the particularities of the SNWRC census, which captured highly mobile individuals that happened to be present at the time of surveys conducted approximately twice per month. Shorebird stopover duration varies by species and by environmental conditions, but is around 10 days (Anderson and Davis 2013), which means that the census may not effectively capture pulses of shorebird migration, however this also avoids recounting the same individuals. Zero and low counts for species were prevalent in the census dataset, while there were fewer observations that captured high abundances (<1.5% of observations containing counts of at least 500 for at least one shorebird species), which could explain the poorer predictive power for higher abundances.

Model uncertainty may also indicate that the selected predictors did not capture other important drivers of habitat use (Jones 2001). For example, water depth is a major determinant of habitat accessibility for shorebirds, with suitable depth ranges varying by species depending on morphological differences (e.g., see Table 6, Baker 1979, Collazo et al. 2002, Taft et al. 2002). Water depth suitability ranges can be measured over larger regions in future using the methods described in Section 5. Alignment between migration timing and food availability is another important consideration; migratory species may be more vulnerable to mismatches than resident species (Sanderson et al.

2006), particularly if there is little individual plasticity to respond to changes in climate and resource conditions (Gill et al. 2013). Invertebrate prey abundances are not currently well understood over large areas and long time-scales, but a better understanding of invertebrate densities in relation to flood frequency patterns that can be measured with remote sensing could one day enable incorporation of this information. Stronger species responses might also be more readily identified if shorebird habitat use were evaluated over a larger area to consider other life stages outside migration. Conditions at breeding and wintering grounds could affect shorebird abundances during migration (Webster et al. 2002); for example, an analysis using stable isotopes found that migration timing for a passerine bird species was determined in large part by conditions in winter habitat (Marra 1998). It is important to consider that SNWRC is one key wetland mosaic that is part of an extended network of wetland stopovers used by shorebirds along the Pacific Flyway.

Results offer some possible prescriptions to improve habitat conditions during spring migration at SNWRC and potentially at other important shorebird stopover sites. We found that water extent was the most important landscape habitat measurement for predicting shorebird abundance at SNWRC wetlands, and that water extent within two kilometers was the most informative. Monitoring water extent in close proximity to existing wetland habitat could be a relatively straightforward target for monitoring and

management of wetland habitat. Wetland management plans, conservation acquisitions, restoration plans, and payment for services programs could also use this two-kilometer distance as a guideline for siting additional flooded habitat. This could be a useful tool for alleviating the shortage of flooded habitat in the Sacramento Valley at the peak of spring migration, which has been identified as a major conservation gap (Dybala et al. 2017, Schaffer-Smith et al. 2017).

#### **4.5 Conclusion**

We analyzed nearly two decades of shorebird habitat use at a globally important wetland stopover site in response to spatiotemporal flooded habitat fluctuations. From this analysis, we learned that shorebirds were more likely to be observed at high abundance when there was a relatively large extent of flooded habitat present at survey locations, and when landscape-level flooded habitat in the vicinity was scarce. Based on study results, human decision-making at multiple hierarchical levels from federal agencies, to local water districts, and individual landowners, can influence shorebird habitat use in the Sacramento Valley. Maintaining a connected wetland habitat network to provide habitat for migratory shorebirds is within our power. Dynamic conservation strategies to provide additional habitat can be implemented as needed through continued monitoring and thoughtful manipulation of the highly engineered surface water distribution systems that are already in place in the Sacramento Valley.

## **5. Conclusion**

### ***5.1 Methodological contributions***

This research has contributed novel methodological innovations that can be widely used in future spatiotemporal studies of hydrological processes and aquatic habitat changes over large areas. Firstly, in the remote sensing analysis, we applied random forest models and receiver operating curves to streamline classification of surface water from stacks of over 3 decades of satellite imagery. The optimization approach provides a standardized and reproducible way to tailor thresholds for landcover classification across a time series of satellite imagery. Secondly, we demonstrated that a weighted interpolation guided by ancillary parcel information can be used to infer flooded habitat in missing data regions, producing very high accuracy classifications from SLC-off Landsat 7 imagery. While most researchers avoid using Landsat 7 imagery due to the ~20% missing data present for images collected since 2003, we were able to incorporate 12 years of data from this sensor in the time series analysis. This interpolation approach can be applied to generate similar high-accuracy surface water classifications in other low-grade agricultural landscapes, where hydrology is heavily manipulated by humans.

Finally, we also developed a simple approach to model individual wetland hydroperiods at high temporal and spatial resolution, relying on precision wetland

topography information. We illustrated how both in-situ water depth measurements and satellite-based water extent maps can be applied to track water depth changes. This method will enable monitoring of water depth over time in non-tidal wetlands at unprecedented spatial and temporal resolution, limited only by the availability of topography data with sufficient vertical accuracy to precisely model fine-scale water depth fluctuations. The resulting spatiotemporal water depth models offer a tremendous advance over two-dimensional classifications of flooded extent, which have previously been widely used as a proxy for habitat suitability for wetland-dependent species.

## ***5.2 Findings and recommendations***

We investigated flooded suitability and shorebird habitat use in response to changes at a globally important stopover site in the Sacramento Valley of California during spring migration. Satellite remote sensing and in-situ measurements were leveraged to estimate total flooded habitat extent across the mosaic of managed wetlands and flood-irrigated agricultural fields and to quantify the accessibility of flooded habitat, as determined by water depth. We then evaluated how shorebird habitat use over nearly two decades responded to multiple scales of habitat fluctuations, human and climate-driven water availability, and land use.

To capture contemporary patterns of regional-scale flooded habitat conditions across the Sacramento Valley, we mapped open water from a 32-year Landsat time

series. We identified a characteristic seasonal scarcity of flooded habitat at the peak of migration, when migrating shorebirds most need to rest and refuel to survive the northward journey to their breeding grounds. We also found that flooded habitat in late March has declined over time. The extent of flooded habitat in wetlands and flood-irrigated agriculture has been sensitive to both climate and land management, particularly in March and April.

To quantify the accessibility of flooded habitat provided in managed wetlands in the Sacramento Valley, which has not previously been described apart from expert opinion, we monitored water depth changes in 23 wetlands within SNWRC. We found that managed wetlands provided much less shallow water habitat than previously thought, with a maximum proportion of 33% shallow water as compared to the 75-90% that was estimated by experts. Yet, habitat gains are possible by changing water level management, to reduce water levels earlier and extend drawdowns in some wetlands to provide more habitat at the peak of migration. We also found that flatter wetlands with more gradual slopes may have a higher capacity to provide habitat. Future conservation acquisitions and restoration plans could prioritize wetlands with these characteristics.

To assess how shorebird habitat use has been influenced by flooded habitat fluctuations, we analyzed nearly two decades of shorebird habitat use at SNWRC in relation to water availability and land management using a generalized joint attribute

modelling approach. We found that shorebird abundance at SNWRC wetlands was likely to be higher when there was more flooding at SNWRC and under low landscape flooded habitat conditions. Results also highlighted the fingerprint of human decision-making as the model fit was higher when incorporating water allocations and water storage controlled by humans, as opposed to climate-driven water availability. We found that flooded habitat extent within 2-10 kilometers of wetlands was the most informative scale at which shorebirds responded to landscape-level habitat changes. Results can inform continued monitoring and siting of new conservation acquisitions or pop-up wetland habitats to support shorebird populations in future droughts through payment for services programs.

### **5.3 Future work**

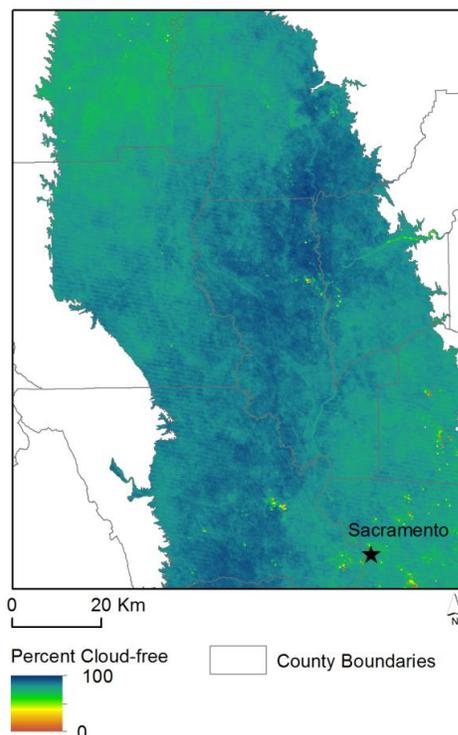
Dynamic water extent and water depth information derived from remote sensing and modelling could contribute valuable information for a variety of applications beyond the themes that explored in this research. For example, wetlands are important in chemical and nutrient cycling processes, climate regulation, water purification, and providing habitat for an incredible array of organisms beyond shorebirds. Wetland hydrology is a key component of how wetlands function and their capacity to provide these services, and with the methods illustrated here it will be possible to incorporate spatiotemporal hydrologic information over broad spatial scales for studies of these

topics. For example, from a biodiversity standpoint, water extent and water depth information could contribute to vegetation community mapping and predicting the distributions of plant and wildlife species that depend on specific aquatic habitats and unique hydrologic regimes. Understanding these dynamic fine-scale hydrologic processes over broader scales could be used to inform the acquisition of conservation properties and in designing wetland restoration projects. These methods can also be used to identify water use optimization opportunities to guide appropriate allocation of limited water resources, and wetland management plans that can meet multiple objectives.

## **Appendix A. Supplementary material for Three decades of Landsat-derived surface water dynamics in an agricultural wetland mosaic; implications for migratory shorebirds**

### ***Appendix A.1 Spatial assessment of Landsat image quality in the study area***

To assess potential spatial aggregation of cloud cover within the Sacramento Valley of California, we stacked the cloud and shadow regions of the Landsat surface reflectance cfmask product (Zhu & Woodcock, 2012) for all spring Landsat images from 1983 – 2015 and tabulated the percent of clear views for each pixel (Fig. S1). Cloud conditions were relatively dispersed, with only isolated areas being persistently affected by clouds (Fig. S1).



**Figure S1: Spatial distribution of cloud-free Landsat surface reflectance pixels within the Sacramento Valley from February to May, 1983-2015. Cloud and shadow regions of the cfmask surface reflectance product (Zhu & Woodcock, 2012) were stacked and the percentage of cloud-free views was tabulated for each pixel in the landscape.**

### ***Appendix A.2 Random forest models used for threshold identification for a single Landsat image***

We conducted random forest models to identify thresholds for mid-infrared surface reflectance, the modified normalized difference water index (MNDWI), and the automated water extraction index (AWEInsh, non-shadow version) for a May 4, 2008 Landsat 5 image, using training and testing data from high-resolution Quickbird imagery acquired on the same date (Appendix A: Table S1). Both models performed

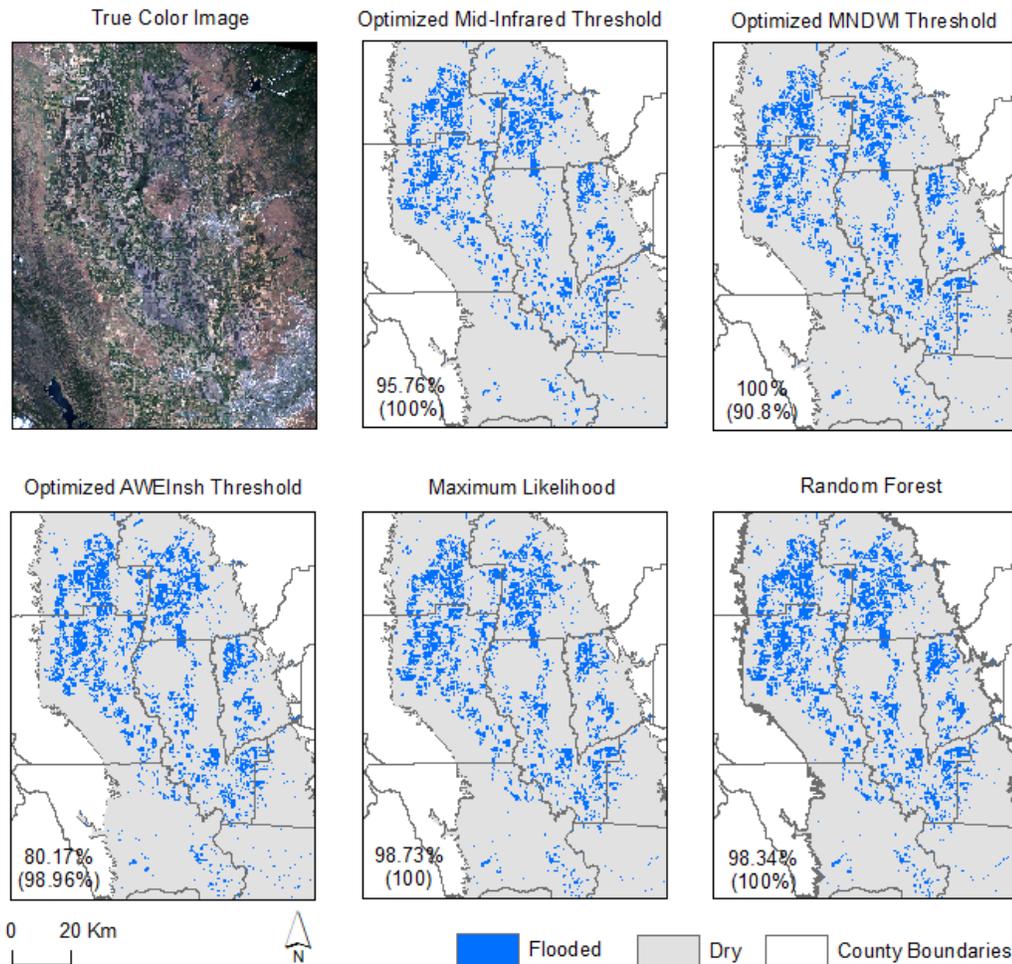
well, but the mid-infrared model was stronger than that for the MNDWI according to multiple measures of fit. The random forest model for mid-infrared data had a lower average out-of-bag error rate, as well as a lower error rate for the water class, as compared to the model constructed for the MNDWI. The area under the curve (AUC) for the mid-infrared model was also higher for the mid-infrared model, indicated better performance.

**Table S1: Identification of thresholds to map water and non-water in the Sacramento Valley from mid-infrared surface reflectance, the modified normalized difference index (MNDWI) and the automated water extraction index (AWEInsh, non-shadow version) for a single Landsat 5 image from May 4, 2008. Random forest models and receiver operating characteristic (ROC) curve analysis were used to identify the optimal thresholds that maximized the true positive rate and minimized the false positive rate. Accuracy was assessed in terms of the error estimates reported by each random forest model, as well as the AUC based on withheld validation data. User's and producer's accuracy for each method are provided in Table 2 in the main text.**

Input data	Random forest model error estimates			ROC curve analysis		Classification accuracy
	Water	Non-water	Average out-of-bag error	AUC	Probability threshold	Overall (%)
Mid-infrared	0.01	0.01	0.01	0.98	0.07	99.5
MNDWI	0.05	0.05	0.05	0.93	-0.32	89.74
AWEInsh	0	0.02	0.01	0.9	-0.38	90.1

### ***Appendix A.3 Comparison of prediction maps for multiple water/non-water classification methods***

We evaluated the performance of multiple classification methods to separate water vs. non-water including: mid-infrared threshold, modified normalized difference water index (MNDWI) threshold, unsupervised classification, maximum likelihood, and random forest classification. We evaluated classifier performance for a May 4, 2008 Landsat 5 image of the Sacramento Valley, using high-resolution Quickbird imagery acquired for the same date to assess accuracy. All methods effectively identified surface water, with a minimum of ~87% accuracy for the water class (Fig. S2).



**Figure S2: Comparison of classification methods to map water and non-water regions of the Sacramento Valley (path/row 44/33) from a May 4, 2008 Landsat 5 image using synchronous high-resolution Quickbird reference imagery for validation. We generated optimized mid-infrared threshold, optimized modified normalized difference water index (MNDWI) threshold, optimized automated water extraction index (AWEInsh, non-shadow version) threshold, supervised classification with maximum likelihood estimation, and supervised random forest classifications. The user's and producer's accuracies for the water class are reported for each approach, with the producer's accuracy shown in parentheses. Note that supervised classifications were reclassified from multiple classes into the water and non-water regions pictured above. DigitalGlobe data used for validation were provided by**

NASA's NGA Commercial Archive Data ([cad4nasa.gsfc.nasa.gov](http://cad4nasa.gsfc.nasa.gov)) under the National Geospatial-Intelligence Agency's NextView license agreement.

### ***Appendix A.4 Water extent variability within the spring season***

Water extent fluctuated substantially in the Sacramento Valley within spring from 1983 - 2015, as indicated by the high levels of variance in the water extent observed within the same two-week period year to year (Fig. 5, Fig. 9, Table 2 in the main text). The minimum water extent consistently occurred in early April, while the maximum typically was observed in late May.

**Table S2: Estimates of open water extent (reported as thousands ha) in the Sacramento Valley of California during spring 1983 - 2015. Estimated mean and standard deviation values were weighted by the proportion of the floodable area that was cloud-free for each image in each two-week period. Each two-week analysis period is designated by its starting month and day.**

<u>Analysis period</u>	<u>Total open water</u>		<u>Agriculture</u>		<u>Herbaceous wetland</u>	
	mean	sd	mean	sd	mean	sd
2-01	106.71	2.33	4.89	37.70	11.16	3.13
2-16	89.28	7.87	67.50	61.11	10.70	3.30
3-01	70.74	0.98	48.06	44.11	11.35	3.20
3-16	30.58	0.85	13.92	17.54	7.91	2.70
4-01	26.09	2.08	11.42	27.86	6.20	3.05
4-16	34.26	0.93	22.92	18.96	3.49	2.45
5-01	95.65	1.67	84.57	41.31	2.44	.97
5-16	144.45	7.65	133.02	25.88	2.15	1.18

## Appendix B. Supplementary material for Quantifying shorebird habitat in managed wetlands by modeling shallow water depth dynamics

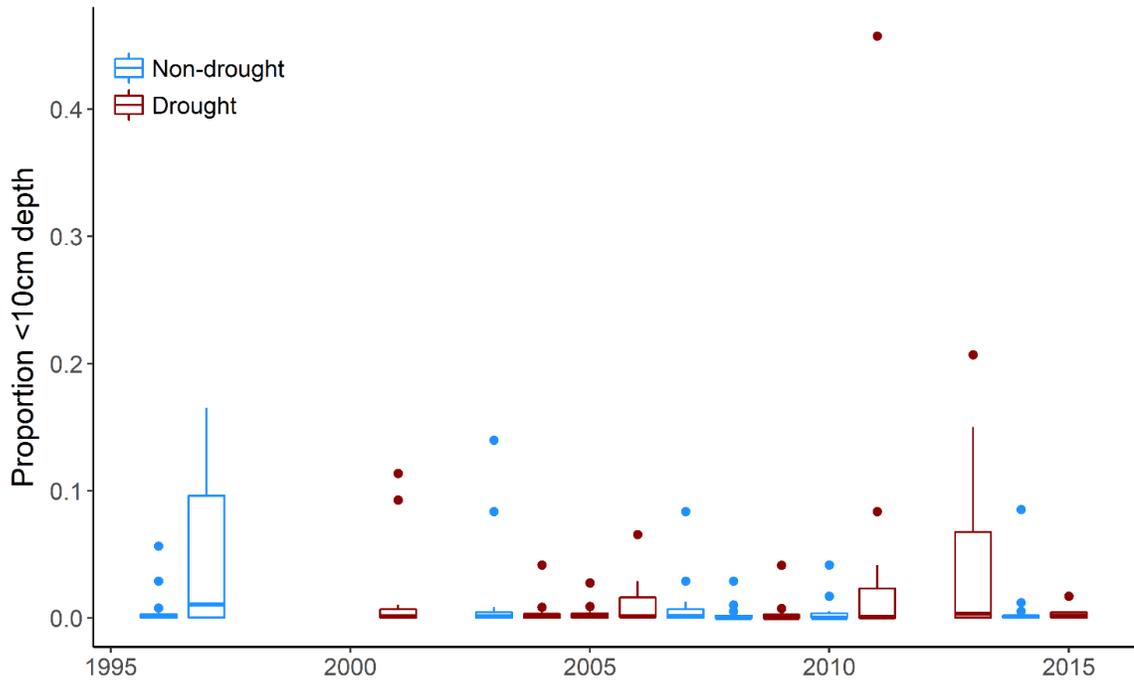


Figure S3: Proportion of peak migration (early April) optimal shorebird habitat (water depth <10 cm) measured across 15 wetlands over drought cycles from 1996-2015. The proportion of optimal habitat was tracked within wetlands using previously generated Landsat-derived water extent maps (Schaffer-Smith et al. 2017). Years designated by the California Department of Water Resources as 'Critically dry', 'Dry', or 'Below normal' were considered to represent drought conditions, while years designated 'Above normal' or 'Wet' were considered to represent non-drought conditions (California Department of Water Resources 2016b).

**Table S3: Wetland characteristics and proportion of optimal habitat (<10cm water depth) under actual and idealized management.**

Wetland	Type	Historic spring shorebird density	Area (ha)	Mean slope variability	sd slope variability	April 1, 2016 Relative volume (ac ft)	April 1, 2016 Proportion <10 cm depth	Ideal relative volume (ac ft)	Potential proportion <10 cm depth	Potential habitat increase (%)
Colusa P3:99	Pond	0.01	8.98	2.55	3.56	0.68	0.06	0.16	0.16	186.59
Colusa T12:2	Seasonal	1.80	1.41	9.00	5.25	0.46	0.02	1.00	0.04	132.17
Colusa T12:3	Seasonal	0.12	7.97	10.41	10.51	0.47	0.00	1.00	0.00	242.11
Colusa T15:1	Seasonal	2.90	3.74	2.20	2.94	0.51	0.24	0.30	0.32	36.30
Colusa T15:2	Seasonal	0.00	6.62	8.49	5.32	0.92	0.03	0.60	0.12	272.56
Colusa T15:3	Seasonal	1.09	0.02	3.36	4.63	0.74	0.09	0.26	0.17	83.45
Colusa T15A:99	Seasonal	0.00	6.16	2.11	3.97	0.83	0.08	0.30	0.50	509.34
Colusa T24:12	Seasonal	0.39	3.94	3.41	5.31	0.73	0.20	0.24	0.25	25.46
Colusa T24:3	Seasonal	0.03	2.66	11.40	10.13	0.22	0.04	0.64	0.07	78.04
Delevan T19:99	Seasonal	0.96	4.03	4.52	5.05	0.68	0.14	0.49	0.17	27.44
Delevan T24:2	Seasonal	3.49	6.98	1.98	3.08	0.98	0.01	0.47	0.25	1677.53
Delevan T30:2	Seasonal	0.09	9.55	5.98	8.01	0.98	0.02	0.36	0.27	1021.12
Delevan T33:99	Seasonal	0.48	4.88	2.69	7.20	0.99	0.04	0.27	0.21	470.36
Delevan T5:1	Seasonal	0.09	.53	4.63	4.32	0.98	0.01	0.69	0.19	1177.94
Sacramento P11:2	Pond	0.00	5.58	5.75	6.81	0.93	0.04	0.31	0.20	344.01
Sacramento P1A:1	Pond	0.60	7.11	4.85	7.93	0.87	0.07	0.61	0.13	92.46
Sacramento T29:2	Seasonal	0.00	3.51	11.43	12.12	0.82	0.10	0.47	0.29	180.99
Sacramento T34:1	Seasonal	58.76	6.65	9.06	14.64	0.57	0.20	0.32	0.27	37.82
Sacramento T4:1	Seasonal	1.45	.94	8.04	8.82	0.67	0.14	0.66	0.14	1.36

Sacramento T4:2	Seasonal	1.01	8.11	5.41	6.92	0.73	0.00	0.92	0.00	71.43
Sacramento T4:3	Seasonal	0.00	.06	8.92	17.51	0.89	0.03	0.24	0.21	577.60
Sacramento T41:1	Seasonal	11.89	5.71	1.67	2.03	0.58	0.13	0.40	0.20	53.72
Sacramento T9:2	Seasonal	0.00	0.89	7.49	9.49	0.06	0.01	0.38	0.08	565.85

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**Appendix C. Supplementary material for Shorebird response to climate, water and land management at multiple scales during spring migration, Sacramento Valley of California, 1997 – 2015.**

***Appendix C.1 Predicted abundance and diversity of shorebirds for Model 1***

a) Discrete abundance

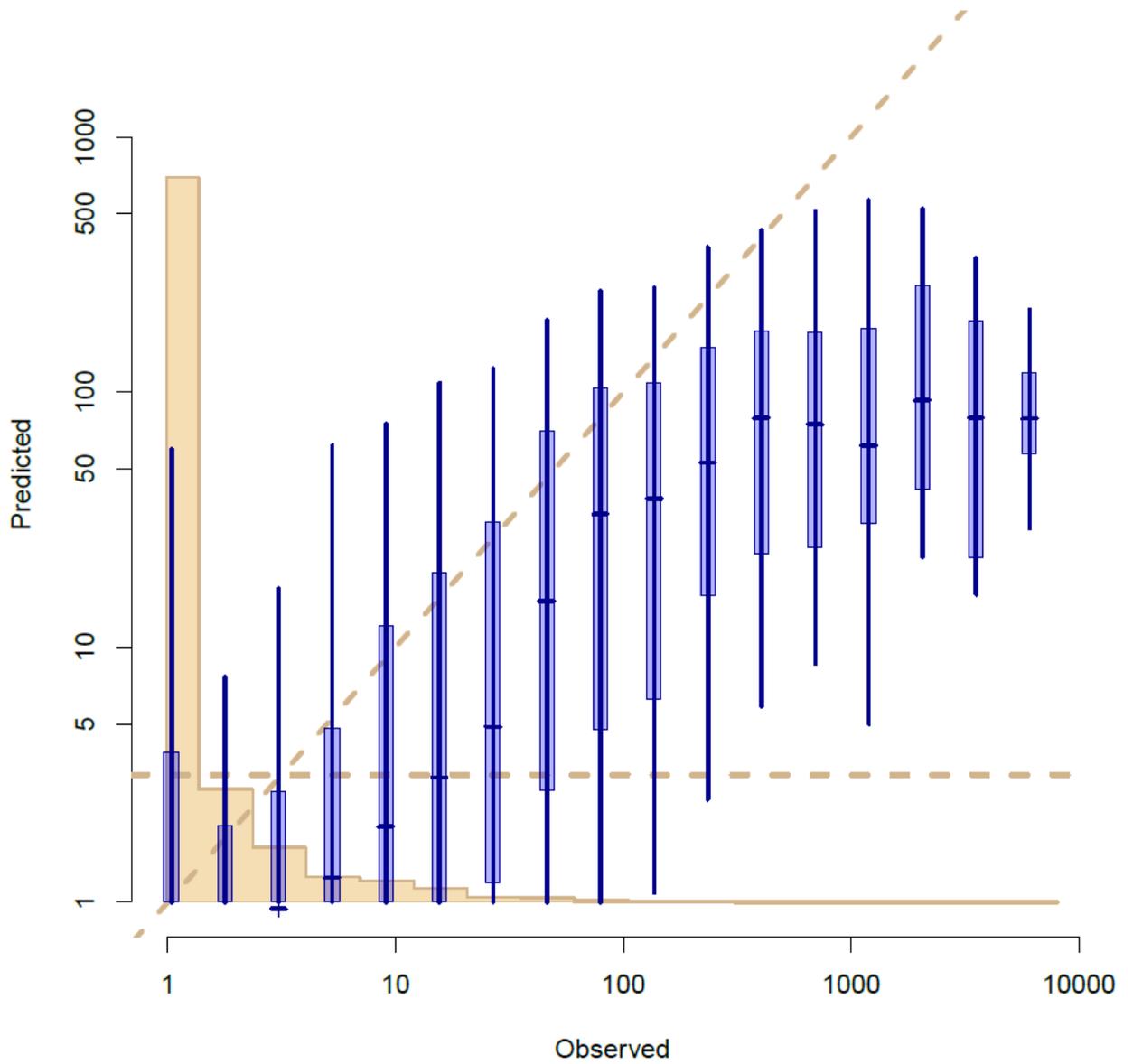
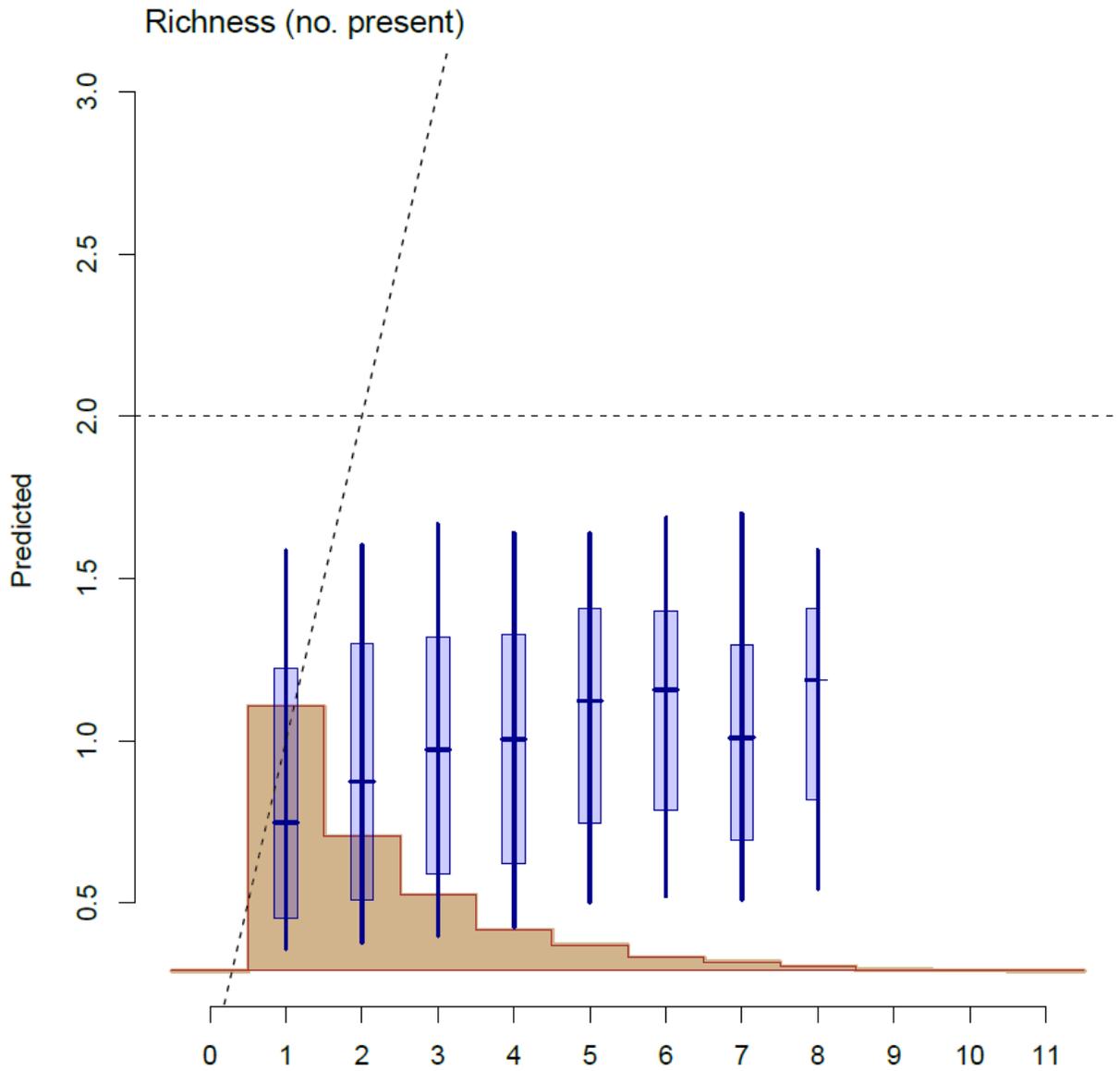


Figure S3: Predicted abundance by species at SNWRC wetland survey locations from Model 1. The blue box plots indicate the average predicted abundance with credible intervals. The tan histogram indicates the distribution of abundance values in the census dataset.



**Figure S4: Predicted species diversity at SNWRC wetland survey locations from Model 1. The blue box plots indicate the average predicted number of species present with credible intervals. The tan histogram indicates the distribution of species diversity values in the census dataset.**

## Appendix C.2 Results for questions about shorebird habitat use drivers from GJAM Models 2-13.

Table S4: Summary of model parameterizations and changes in model fit compared to Model 1. Variables are described in the main text for the chapter.

<i>What is the relative importance of spring periods and habitat conditions in the study area?</i>			
<b>Model number</b>	<b>Model parameterization</b>		<b>DIC</b>
1	Abundance, 19 species	period marsh + acflood + w.aggregation + w.mean.pa.ratio + w.extent + ndvi	-6263731
<i>Does the interaction between spring time period and water extent matter?</i>			
<b>Model number</b>	<b>Model modifications</b>		<b>DIC</b>
2	Abundance, 19 species	+ w.extent*period	-6431691
<i>Does water availability matter? Is surface water availability, drought intensity, reservoir storage, or water allocation more important?</i>			
<b>Model number</b>	<b>Model modifications</b>		<b>DIC</b>
3	Abundance, 19 species	+ wy.index	-6334689
4	Abundance, 19 species	+ drought	-6383904
5	Abundance, 19 species	+ consec.drought	-6230575
6	Abundance, 19 species	+ storage	-6388306

7	Abundance, 19 species	+ supply.ag	-6556328
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*Does the land use matter? What is the relative importance of flooding on agricultural land and flooding in emergent wetlands?*

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<b>Model number</b>	<b>Model modifications</b>		<b>DIC</b>
8	Abundance, 19 species	w.aggregation, w.mean.pa.ratio, and w.extent calculated only for agricultural land mapped by the National Landcover Dataset.	-6352994
9	Abundance, 19 species	w.aggregation, w.mean.pa.ratio, and w.extent calculated only for wetlands mapped by the National Landcover Dataset.	-6503708

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*At what spatial scale are shorebirds responding to changes in water extent on the landscape?*

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<b>Model number</b>	<b>Model modifications</b>		<b>DIC</b>
10	Abundance, 19 species	w.extent within 1 km, rather than 5 km.	-6142942
11	Abundance, 19 species	w.extent within 2 km, rather than 5 km.	-6425287
12	Abundance, 19 species	w.extent within 10 km, rather than 5 km.	-6293332
13	Abundance, 19 species	w.extent within 15 km, rather than 5 km.	-6154004

**Table S5: Significance and direction of response by species to the interaction of total water extent measured within five km of wetland survey locations and different time periods within spring. Species are indicated by four-letter codes (see Table 4). (+) indicates a significant positive response, while (-) indicates a significant negative response to larger values of a given variable.**

Species	Spring periods						
	Feb01	Feb16	Mar01	Mar16	Apr01	Apr16	May
BBPL				-			
SPPL						+	
KILL			-	-		+	
BNST		-	-	-	-		
AMAV							
GRYE							
LEYE							
SOSA							
WILL							
SPSA							
WHIM				-			
LBCU							
WESA				-			
LESA				-			
DUNL				-			
DOWI				-	-	-	
WIPH							
RNPH						+	
COSN							

**Table S6: Significance and direction of response by species to regional water availability predictors used in Models 3-7. Species are indicated by four-letter codes (see Table 4). Variables are described in Table 2. (+) indicates a significant positive response, while (-) indicates a significant negative response to larger values of a given variable.**

Species	Water availability variable (Model run)				
	wy.index (3)	drought (4)	consec.drought (5)	storage (6)	supply.ag (7)
BBPL					
SPPL		+	+	-	-
KILL					
BNST					-
AMAV					+
GRYE					
LEYE		-		+	+
SOSA					
WILL					
SPSA					
WHIM					+
LBCU					
WESA		+	+		
LESA	-	+	+	-	
DUNL		+	+		
DOWI					
WIPH					
RNPH				-	
COSN	+				+

**Table S7: Significance and direction of response by species to water extent measured within 5km from SNWRC wetland survey locations in agricultural lands and emergent wetlands mapped by the National Landcover Dataset (Models 8-9). Species are indicated by four-letter codes (see Table 4). Variables are described in the main text. (+) indicates a significant positive response, while (-) indicates a significant negative response to larger values of a given variable.**

Species	Model run (land cover) regional flooded habitat variables					
	8 (agriculture)			9 (emergent wetland)		
	w.aggregation	w.mean.pa.ratio	w.extent	w.aggregation	w.mean.pa.ratio	w.extent
BBPL						-
SPPL	+				+	-
KILL	+	+		-	+	-
BNST			-			-
AMAV						
GRYE	+	+			+	-
LEYE	+				+	
SOSA						
WILL						
SPSA						
WHIM		+				
LBCU						-

WESA	+	+		+	-
LESA	+	+		+	-
DUNL				-	
DOWI	-				
WIPH					
RNPH	+				
COSN	+		+	+	-

**Table S8: Significance and direction of response by species to different scales of measurement for regional water extent used in Models 10-13. Species are indicated by four-letter codes (see Table 4). (+) indicates a significant positive response, while (-) indicates a significant negative response to larger values of water extent.**

Species	Scale of water extent predictor (Model run)			
	1 km (10)	2 km (11)	10 km (12)	15 km (13)
BBPL			-	-
SPPL				
KILL	-	-	-	
BNST	-	-	-	-
AMAV	+			
GRYE	-	-	-	-
LEYE				
SOSA				
WILL				
SPSA	-	-		
WHIM				
LBCU				
WESA			-	
LESA			-	
DUNL	+	+	-	-
DOWI				
WIPH				
RNPH				
COSN				

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## Biography

Prior to the doctoral program at Duke University, Danica Schaffer-Smith earned a B.S. in Environmental Science from the University of Redlands (2006) and a Master of Environmental Science and Management specializing in Conservation Planning from the Bren School of Environmental Science and Management at UC Santa Barbara (2010).

## Publications

**Schaffer-Smith, D.**, Swenson, J.J., Barbaree, B.A., & Reiter, M.E. 2017. Three decades of Landsat-derived spring surface water dynamics in an agricultural wetland mosaic; Implications for migratory shorebirds. *Remote Sensing of Environment*, 193: 180-192. doi: 10.1016/j.rse.2017.02.016

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## Scholarships, Fellowships, and Honors

- P.E.O. Scholar Award (2017)
- Graduate School Summer Research Fellowship (2017)
- Graduate Training Enhancement Grant, NCAR Data Analytics Workshop (2016)
- NSF Doctoral Dissertation Research Improvement (2015)
- Graduate School Domestic Travel Award (2015)
- NASA-MSU Professional Enhancement Award (2014)
- NASA Earth and Space Science Fellowship (2013)

- Center for Latin American Studies Mellon Research Travel Grant (2013)
- Bren School Corporate Partners Fellowship (2009)
- Monica Florian Prize (2008)