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Using High Resolution Satellite and Telemetry Data to Track Flooded Habitats, Their Use by Waterfowl, and Evaluate Effects of Drought on Waterfowl and Shorebird Bioenergetics in California

Open-File Report 2020–1102

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Cover Photo: Photograph of a U.S. Geological Survey biologist attaching a backpack-mounted and solar-powered GPS-GSM transmitter to a male mallard in the Suisun Marsh of California. Transmitters, like the one shown, allow researchers in the Western Ecological Research Center of the U.S. Geological Survey to track and record waterfowl locations and movements and to understand potential impacts of factors including drought on the populations of these birds. Photograph taken on April 13, 2017, by Michael Casazza, U.S. Geological Survey.

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Conversion Factors

International System of Units to U.S. customary units

Multiply	By	To obtain
	Length	
centimeter (cm)	0.3937	inch (in.)
meter (m)	3.281	foot (ft)
kilometer (km)	0.6214	mile (mi)
meter (m)	1.094	yard (yd)
	Area	
hectare (ha)	2.471	acre
hectare (ha)	0.003864	square mile (mi^2)
	Mass	
gram (g)	0.03527	ounce, avoirdupois (oz)

Datum

Point Blue Conservation Science open-water dataset: World Geodetic System 1984 (WGS 1984).

Duck telemetry dataset: World Geodetic System 1984 (WGS 1984).

Preface

Wetland managers in the Central Valley of California, a dynamic hydrological landscape, require information regarding the amount and location of existing wetland habitat to make decisions on how to best use water resources to support multiple wildlife objectives, particularly during drought. Scientists from the U.S. Geological Survey Western Ecological Research Center (WERC), Point Blue Conservation Science (Point Blue), and the U.S. Fish and Wildlife Service (USFWS) partnered to learn how wetland and flooded agricultural habitats used by waterfowl and shorebirds change during the non-breeding season (July–April) particularly during drought. During extreme drought conditions, the ability to provide sufficient water for wildlife often depends on the timing of water deliveries to managed wetlands and winter-flooded crop fields and decisions on whether to fallow croplands. Waterfowl and shorebirds could be particularly affected by these decisions because they typically rest and feed in flooded habitats. Poor habitat conditions resulting from spatially or temporally suboptimal water deliveries (that is, mismatch between waterfowl habitat needs and timing and location of flooded habitats) could reduce waterfowl hunting opportunities and body condition. Point Blue scientists developed a system for near real-time tracking of habitats used by waterfowl, shorebirds, and some other wetland-dependent "waterbirds" (www.pointblue.org/watertracker) and to assess the impacts of drought on habitat availability and on waterfowl and shorebird bioenergetics. The WERC researchers linked these data with near real-time tracking (telemetry) data of duck locations throughout the Valley. The team used these two datasets to relate duck locations to open-water characteristics and to learn how waterfowl use habitats under spatially and temporally changing conditions during drought and non-drought periods. We found that recent extreme drought (2013–15) significantly changed the timing and magnitude of flooding and consequently reduced the availability of habitats used by waterfowl and shorebirds more than other recent historic droughts 2000–11. Drought reduced irrigations of moist soil seed plants and thus there was lower food energy available for waterfowl. Analyses using bioenergetics models indicated that, overall, extreme drought increased food energy deficits (total number of deficit days) for shorebirds and waterfowl. Our analysis indicated a strong direct relationship between duck locations and classified habitat derived from open-water data during the wintering period (October–March). This result helps confirm the application of dynamic water data to identify flooded areas that provide waterfowl habitat. Presence of open water at a 1-hectare resolution can be used effectively to identify flooded landscape areas available as habitat for ducks. Our discoveries from evaluating use of space by ducks also indicated that nighttime feeding locations of ducks were concentrated nearby primary roosts and that foraging distances could depend on hydrologic dynamics of location (Suisun Marsh versus California excluding Suisun Marsh) and time of season (early, middle, late). Other results indicated that some areas on the California landscape with extremely reliable water supplies could receive consistent use by ducks year after year (in essence, almost drought proof). The Water Tracker is set up to automatically track wetland habitat and food availability each year and is making these data available to water and wetland managers. Results from this research are a significant step toward understanding how waterfowl and shorebird habitats can be optimally managed on the landscape to support desired populations of these migratory birds during extreme drought.

Abbreviations

AIC	Akaike's Information Criterion
CVJV	Central Valley Joint Venture
CVPIA	Central Valley Project Improvement Act
GPS	Global Positioning System
LTA	long-term average
NDVI	Normalized Difference Vegetation Index
Point Blue	Point Blue Conservation Science
USFWS	U.S. Fish and Wildlife Service
USGS	U.S. Geological Survey
WERC	Western Ecological Research Center (USGS)

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Chapter A. Waterfowl and Shorebird Habitats, Drought, and Related Research in California's Central Valley

By Matthew Reiter and Dennis Jongsomjit

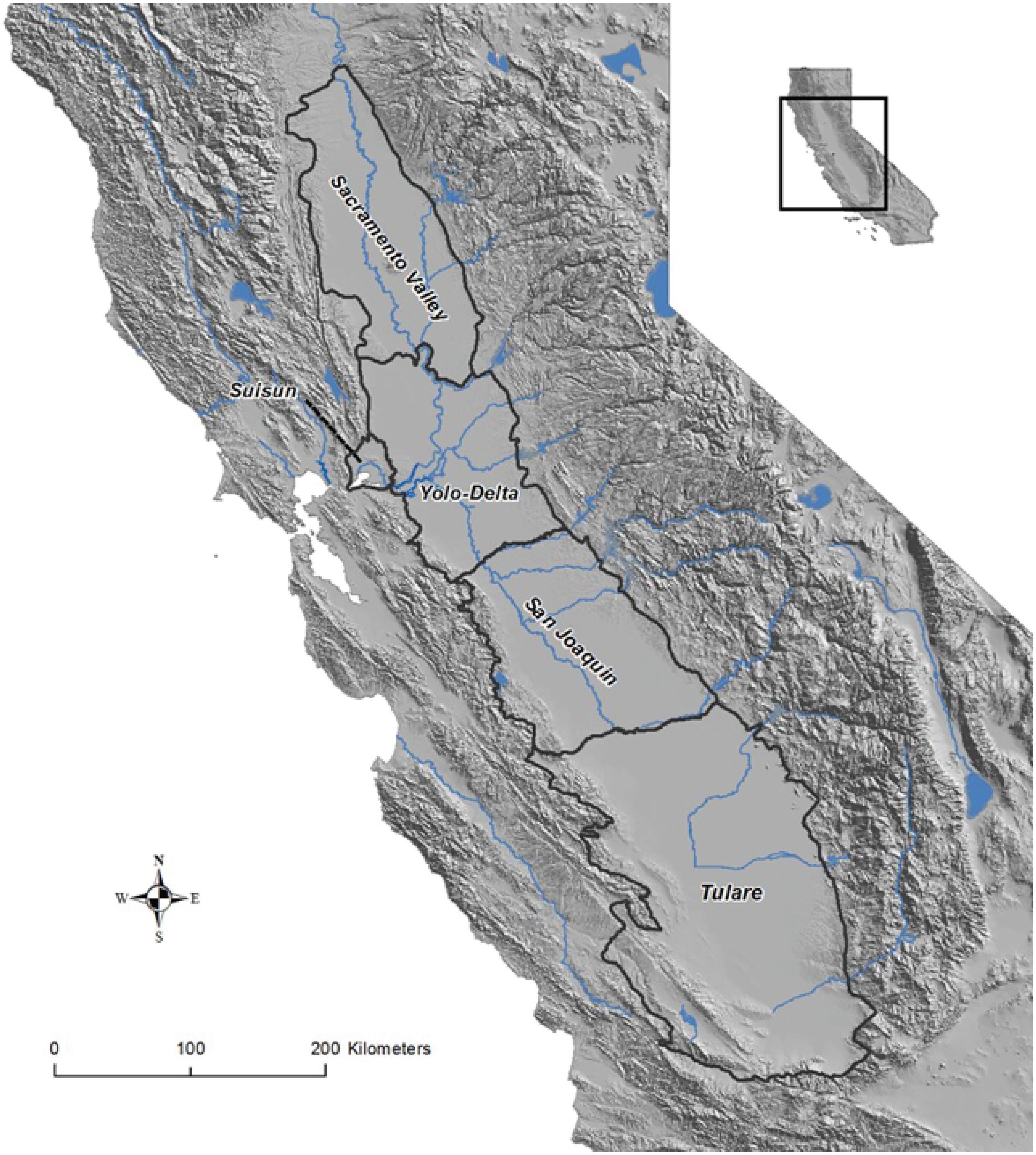
Introduction

The Central Valley is a nexus for water resources in California and drains the Sacramento and San Joaquin River watersheds (fig. A1). The distribution of water in the Central Valley is highly managed and driven by an extensive network of canals, levees, and pumps developed as part of the Central Valley Project and the California State Water Project in the early to mid-20th century (Hanak and Lund, 2012). Urban centers, agriculture, and the environment compete for limited water (Hanak and Lund, 2012), and the Sacramento River and San Joaquin River watersheds are projected to experience increased demand for water due to population growth and agricultural intensification. At the same time, water supply availability in these watersheds may change due to variability in temperature and precipitation patterns as reflected in drought periods (Snyder and others, 2004; California Department of Water Resources, 2009; Hanak and Lund, 2012). During the 2012–16 drought, the most severe in California's recorded history based on several metrics, water supplies were extensively reduced for managed habitats used by waterfowl, shorebirds, and other wildlife (Diffenbaugh and others, 2015; for example, National Wildlife Refuges [see years 2014 and 2015] in U.S. Bureau of Reclamation, 2018).

Migratory waterfowl (Order: Anseriformes; Family: Anatidae; Sub-Family: Anatinae) and shorebirds (Order: Charadriiformes; Family: Charadridae, Scalopacidae, Recurcvirostridae, Haemotopodidiae) rely on the water and wetlands of the Central Valley for habitat (Gilmer and others, 1996; Central Valley Joint Venture, 2006), despite that more than 90 percent of the historically occurring natural wetland habitat has been replaced with agriculture and human developments (Frayer and others, 1989). However, flooded post-harvest rice, corn, and possibly other field crops (for example, wheat and tomatoes) provide substantial "surrogate" feeding habitat (Elphick and Oring, 1998; Fleskes and others, 2012; Strum and others, 2013) in addition to the extensive network of restored and managed wetlands, which are used for roosting and feeding. The Central Valley Joint Venture (CVJV), a partnership of federal and state agencies and non-governmental organizations focused on bird habitat conservation in the Central Valley, requires information on habitat availability for conservation planning (Central Valley Joint Venture, 2006). Similarly, habitat managers require spatiotemporal information on habitat distributions, as well as waterfowl distributions, to provide adequate habitat for waterfowl.

Avian bioenergetics modeling previously indicated that under severe drought, availability of flooded habitat is a limiting factor for providing adequate food for wintering ducks in the Central Valley (Central Valley Joint Venture, 2006; Petrie and others, 2016). Such food energy deficits would likely compromise the physical condition and subsequent reproduction and survival of waterfowl (Miller, 1986; Conroy and others, 1989; Raveling and Heitmeyer, 1989; Fleskes and others, 2016) and survival of shorebirds (Morrison and others, 2007). Empirically based estimates of water distribution and habitat availability would allow improved assessment of habitat limitations derived from bioenergetics models, especially when coupled with waterfowl distribution information. Likewise, water and waterfowl distribution information can help to identify water-management solutions in the face of extreme drought by identifying where habitat is most needed.

Waterfowl and shorebird habitats vary in quality for feeding or roosting depending on land-management practices (whether they are flooded, timing of flooding, and the composition of surrounding habitats), which greatly determines if they will be utilized by birds. Drought affects decisions made by wetland managers and farmers in the Central Valley regarding the timing and duration that wetlands and croplands are flooded during fall–winter. Furthermore, reductions in summer irrigation of seasonal wetlands can lead to reduced seed availability and consequently, a reduction in waterfowl food resources (Naylor, 2002). Also, during fall and winter waterfowl are more concentrated in landscapes that provide abundant flooded habitat and food resources and are associated with flooded croplands and wetlands within these landscapes (Davis and others, 2014). The magnitude of changes in the type of wetlands and irrigation regimes from drought or changes in water availability is not known and could vary spatially. Therefore, a better understanding is needed about how water resources are applied to wetlands on the landscape in drought and non-drought years and the implications for the waterfowl and shorebirds that rely on these habitats.



Base modfied from U.S. Geological Survey and Central Valley Joint Venture (U.S. Fish and Wildlife Service). Reiter and others, 2018; DOI:10.7717/peerj.5147/fig-1

Figure A1. Central Valley study area in California, United States. The Central Valley Joint Venture boundaries and five basins of the Central Valley: Sacramento Valley Basin, Sacramento–San Joaquin River Delta [Yolo–Delta], San Joaquin Basin, Suisun Basin, and Tulare Basin, California. Data source: U.S. Geological Survey (USGS) and Central Valley Joint Venture (U.S. Fish and Wildlife Service). Citation: Reiter and others, 2018.

Monitoring the highly dynamic and variable distribution of water, wetlands, and winter-flooded crop habitats in the Central Valley requires data at a fine spatial and temporal resolution but also across a broad spatial and temporal extent. Remote sensing is a valuable resource for tracking land cover changes and ecological processes (Ustin, 2004). The Landsat Mission (U.S. Geological Survey, 2007) provides spatial imagery that can be used to quantify the distribution of open surface water every 16 days at a resolution of 30-meter pixels across the majority of the Earth. Open-water datasets developed by Point Blue and The Nature Conservancy (Veloz and others, 2012; initially funded through the California Landscape Conservation Cooperative) provide a foundation to explore the impacts of drought on wetlands in the Central Valley.

Technological advancements in Global Positioning System (GPS) telemetry markers allow almost real-time observation of waterfowl movements and habitat selection as well as enabling quantification of metrics used as inputs in avian bioenergetics models. A current project conducted by the Western Ecological Research Center involves using GPS transmitters to track and record coordinate locations for multiple species of waterfowl in Suisun Marsh during breeding and non-breeding seasons. Our ability to leverage this information during a period of climatic extremes offers an unparalleled opportunity to gain insight into waterfowl habitat selection and the man-made decisions (for example, water-delivery timing and location) that influence them.

When combined, telemetry data on ducks marked with GPS transmitters can be used to evaluate performance of remote sensing data for classifying habitats that are flooded and available for waterfowl. Importantly, high-resolution telemetry data recorded in near real-time can provide information on waterfowl responsiveness to water-management decisions intended to provide adequate habitat for waterfowl. Of the potential “available” habitat, habitat that is available to waterfowl could be highly variable as a function of bird behavior (determined using telemetry). Without water and habitat management being well informed with data on the distribution and abundance of habitat, food resources may be insufficiently available or inappropriately distributed to support target waterfowl populations under conservation objectives. To address uncertainty in habitat conditions and to inform management of water for habitats, our telemetry data can be used to understand which available habitats are most likely to be used and how timing and location of flooding can be optimally managed to support wintering waterfowl populations.

We applied existing water-distribution data in combination with wetland vegetation distribution data and indices to vegetation greenness (for example, Normalized Difference Vegetation Index [NDVI]; Crippen, 1990), to delineate between irrigated seasonal wetlands, non-irrigated seasonal wetlands, semi-permanent wetlands, and flooded agriculture to understand the influence of drought on waterfowl and shorebird bioenergetics and movements. We conducted analyses of satellite imagery to identify how drought influences available wetland habitat types and the duration of flooding. Next, we used existing bioenergetics models to assess the impact of changing wetland availability as the result of drought on meeting waterfowl and shorebird conservation objectives to meet population objectives for both groups, following Petrie and others (2016), Dybala and others (2017), and Central Valley Joint Venture (unpub. data, 2020). We integrated the tested wetland classification heuristics with automated classifications of Landsat 8 satellite data to calculate wetland and food energy availability in near-real-time at several spatial scales as an ongoing tool to inform and evaluate water allocation decisions for wetlands and waterfowl. Lastly, we combined tracking data for ducks with the dynamic habitat availability data to assess the effectiveness of the water and wetland tracking data and to understand what factors influenced use of habitats by waterfowl.

Study Area

We considered the CVJV primary planning region (Dybala and others, 2017) to be the focal area for this study. We divided up the region into five basins according to Shuford and Dybala (2017) and used only the Sacramento Valley Basin and the San Joaquin Basin for some analyses (fig. A1). The Central Valley is in the Great Valley ecoregion (Hickman, 1993, p. 45) and extends greater than 400 kilometers (km) north to south and up to 100 km east to west; bounded by the Sierra Nevada, Cascade, and California Coastal Range mountains. The Central Valley climate generally is cooler and wetter in the north (Sacramento Valley Basin) than in the south (San Joaquin Basin and Tulare Basin). Water allocation and use in the Central Valley is highly managed, and the southern portion of the Valley often relies on water being transferred for use from the north through contractual agreements (“water transfers;” Hanak and Lund, 2012). Consequently, there generally is less flooded agriculture in the southern Central Valley and higher year-to-year variability in flooding compared to the north (Reiter and others, 2015). Most of the surface water in the Central Valley originates from snowpack in the adjoining Sierra Nevada and Cascade mountains (Carle, 2009).

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Chapter B. Objective 1: Identify How Drought Influences Available Wetland Habitat Types and the Duration of Flooding

By Matthew Reiter and Dennis Jongsomjit

Introduction

Drought likely affects the composition of managed wetland types on the landscape in the Central Valley because the timing and duration of flooding largely determines the hydroperiod of managed wetland (Central Valley Joint Venture, 2006); seasonal wetlands are often flooded October–March whereas semi-permanent wetlands are inundated October–August. Additionally, with limited water supplies, the abundance of non-irrigated seasonal wetlands likely increases whereas irrigated seasonal and semi-permanent wetlands are likely to decline (Petrie and others, 2016). Because the food value of each wetland type is different (irrigated seasonal wetlands have higher moist soil seed biomass and therefore are considered higher quality for waterfowl than non-irrigated seasonal wetlands [Naylor, 2002]), their relative composition is important for understanding the capacity of the landscape to support waterfowl and shorebirds. Additionally, the composition of wildlife-friendly agriculture practices is likely to change. During drought, we anticipate that, similar to managed wetlands, the total quantity (area) of post-harvest flooded agriculture that provide habitat (rice [shorebirds and waterfowl], corn [shorebirds and waterfowl], and field and row crops [shorebirds]) would decline and flooding duration would be reduced.

Methods

Classifying Wetland Type

To explore how drought influenced the composition of wetlands on the landscape and ultimately food resources, we evaluated three types of managed wetlands (semi-permanent/permanent, irrigated seasonal, and non-irrigated seasonal; unmanaged wetlands excluded) using a combination of geographic information system (GIS) layers. Layers included wetland areas mapped in 2009 (Petrik and others, 2014), land cover from National Land Cover Database mapped in 2001 (Homer and others, 2007), distributions of open-water (Veloz and others, 2012), classified Landsat 5 data for January–December in years 2000–11, classified Landsat 8 imagery April 2013–April 2015 (Reiter and others, 2018), indices of vegetation greenness (Normalized Difference Vegetation Index; NDVI), and legacy management and spatial data from managers of wetland areas and National Wildlife Refuges.

To distinguish seasonal and semi-permanent/permanent wetlands from other common land cover classes in wetland complexes (table B1), we assessed the following heuristic applied by Petrik and others (2014) by using time series of monthly water data (Reiter and others, 2018). If a wetland pixel was classified as wet in open-water data in specific combinations of months, it was classified as a seasonal or semi-permanent/permanent wetland. To be classified as semi-permanent/permanent, a pixel must be wet in at least 1 month during each of the three periods: (1) December–January; (2) May–July; and (3) August–September. If a pixel was only flooded in January or December, it was classified as a seasonal wetland. We used random forest classification and regression trees (Breiman, 2001) and ground validation data from the Sacramento National Wildlife Refuge complex (greater than 300 management units per year 2000–11) to develop these models.

To match the pixel level heuristic classes with management unit level classifications, we derived the proportion of pixels in each unit that were considered seasonal and the proportion that were considered semi-permanent/permanent as covariates in our model. This was our base model. We then sought to enhance this initial base heuristic model and considered the annual pattern of open water. We included the mean monthly probability of open water from the whole year in the wetland unit, the maximum probability of open water across the year, and the standard deviation of the probability of open water across the year. Because a wetland can, theoretically, be considered permanent if only one pixel was flooded in all months, we included a single level factor indicating if there were any semi-permanent/permanent pixels within a unit. We used the Base model and Base Plus model to classify five land cover types and classify only three types (table B1) where all the unmanaged land cover types (unmanaged wetland, upland, and forest) were combined. We used a random subset of 70 percent of our data to train the model and the remaining 30 percent to test it.

Table B1. Summary of land cover types considered in random forest classification models of dominant wetland management type in the Sacramento National Wildlife Refuge, California, United States.

Cover type	Code
Seasonal wetland group	
Seasonal flooded marsh	SFM
Irrigated seasonal flooded marsh	ISFM
Watergrass	WG
Semi/permanent group	
Summer water	SW
Permanent pond	PP
Unmanaged wetland group	
Dry wetland	DRY
Irrigated dry wetland	IDRY
Unmanaged freshwater wetland	UFW
Alkali meadow	AM
Vernal pool—Alkali meadow complex	VPAM
Uplands group	
Annual grassland	AG
Vernally wet annual grassland	VAG
Perennial grassland	PG
Irrigated pasture	IP
Valley oak savanah	VOS
Forest group	
Mixed riparian forest	MRF
Cottonwood willow	CW
Riparian willow scrub	RWS
Other	
Arrundo donax	ARRUNDO
Ditch/canal	DTCH
Facilities	FAC

To distinguish between irrigated and non-irrigated seasonal wetlands, we developed a binomial boosted regression tree model (Elith and others, 2008) with the 'dismo' package (Hijmans and others, 2017) in the program R v3.3.3 (R Core Team, 2018) using the NDVI values in wetland units from three months (July, August, and September). Normalized Difference Vegetation Index data were calculated from the U.S. Geological Survey (USGS) Landsat 5 Thematic Mapper (TM) top-of-atmosphere (TOA) reflectance 8-day scenes and Landsat 8 Operational Land Imager (OLI) imagery downloaded from Google Earth Engine (Gorelick and others, 2017) and the data from both products were averaged within each month. We hypothesized that irrigated seasonal wetlands would have, on average, a higher level of the NDVI in July, August, and September compared to non-irrigated seasonal wetlands and thus allow them to be individually identified. Because we were interested in whether seasonal marshes were irrigated or not, we filtered units used to train the model to only those that had some seasonal marsh as indicated in the yearly management data. For modeling purposes, units that had any irrigated seasonally flooded marsh were then marked as irrigated and units that had no irrigated seasonally flooded marsh were marked as not-irrigated.

Following Elith and others (2008), we ran an initial set of exploratory models to assess a range of tree complexity (1–5) and learning rate (0.01, 0.005, 0.001) parameters for our models because selecting the optimal combination of these parameters can influence model fit. To estimate an NDVI threshold value for distinguishing irrigated from non-irrigated seasonal marsh, we selected the combination of tree complexity (3) and learning rate (0.01) parameters that resulted in the largest reduction of deviance in the model fit. We initially calculated the NDVI thresholds to convert our predicted probability of irrigation for a given wetland unit into irrigated =1 and non-irrigated =0 based on minimizing the difference in sensitivity and specificity of our model predictions (Liu and others, 2005). However, our initial assessment highlighted that this threshold (0.187) could overpredict irrigation (fig. B1, model predicted [*B*] versus observed [*A*]) so we explored the minimum difference-based threshold and incrementally added 0.01–0.4 and then assessed the predicted versus observed irrigation values (fig. B1, calibrated [*C*] versus observed [*A*]).

We applied our model classifications (across all areas classified) as managed wetlands in the 2001 (Homer and others, 2007) and 2009 (Petrik and others, 2014) valley-wide wetland base layers to generate a relative composition of wetland types for each year during 2000–17. Because our models (wetland type and irrigation) were based on ground truth data from wetland units instead of individual pixels, and management generally is unit by unit, we used a 2009 wetland boundary layer and wetland footprint (Petrik and others, 2014) coupled with a wetland layer from 2001 (Homer and others, 2007) to define the set of units to use in prediction of irrigation. Any polygon that had greater than 0.5 change in the proportion of wetland between 2000 and 2009 was removed, and we further filtered polygons to include only those polygons with greater than 50-percent area classified as wetland in 2009. Using the set of areas identified as wetland pond units, we calculated the mean of NDVI values across pixels within wetland units for each of July, August, and September of each year (2000–17). Then, using the modeled NDVI threshold for predicted wetland irrigation, wetland units were classified as irrigated or non-irrigated.

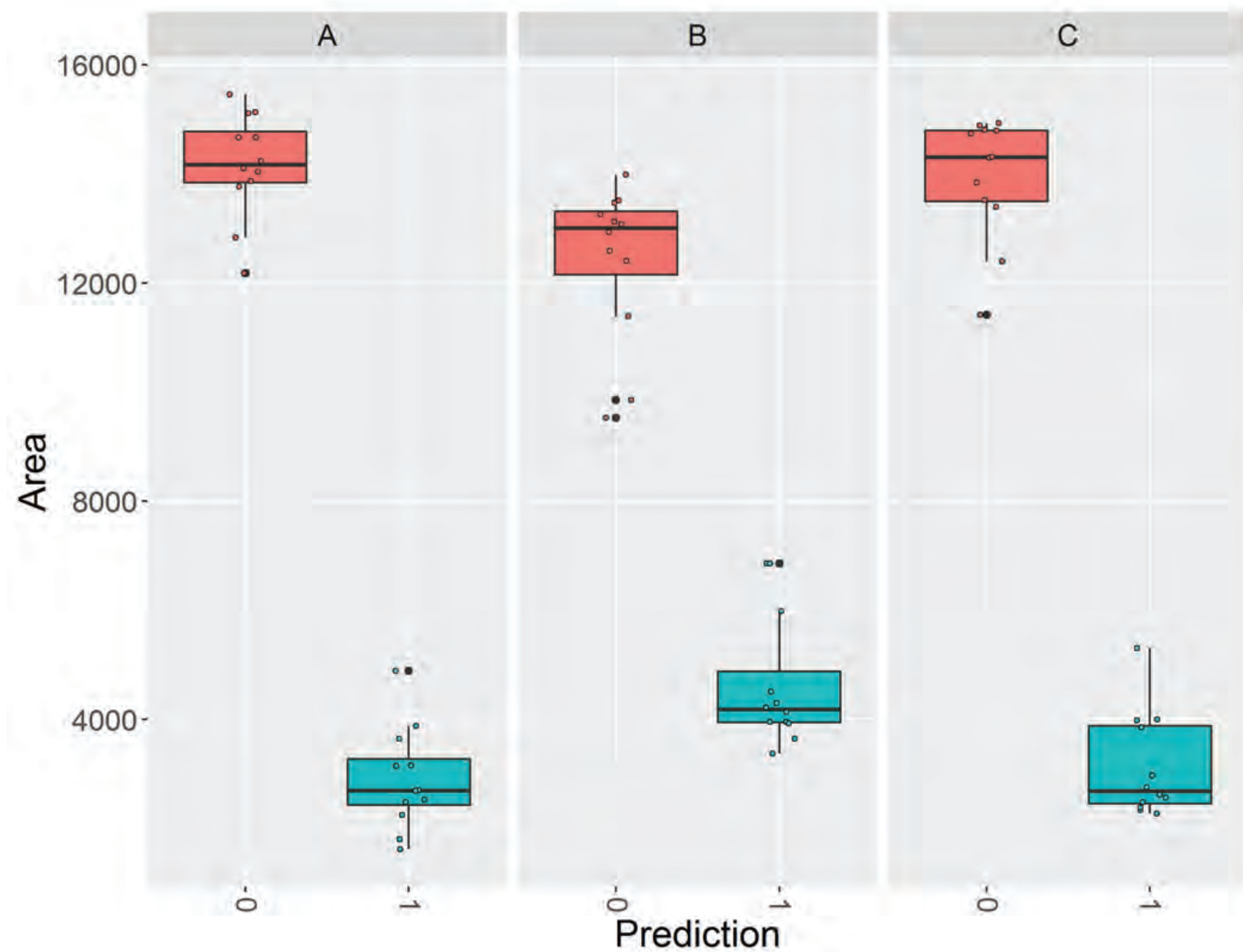

Figure B1. Summary of threshold calibration for classifying irrigated (1) and non-irrigated (0) seasonal wetlands using management data from the Sacramento National Wildlife Refuge Complex (2000–11). Box plots identify the median (50th percentile; center line) and the 25th and 75th percentiles (top and bottom of box, respectively) of the observed data. Plot whiskers extend to 1.5 times the interquartile range. Points dispersed among plots are the observed data.

Drought Analysis

To understand how drought influenced the timing and abundance of open water in habitats (seasonal and semi-permanent wetlands, rice, corn, field and row crops), we overlaid the open-water data (Reiter and others, 2018) on existing data layers of the distribution of planted rice and corn (The Nature Conservancy, unpub. data, 2015), as well as on managed wetlands (National Land Cover Database, Homer and others, 2007; Petrik and others, 2014), to see how the availability of flooded habitats used by shorebirds and waterfowl changed through the year and from drought. We used generalized additive mixed models to assess the probability of open water as a function of cover type, drought year (2001–02, 2007–09), extreme drought year (2013–15), non-drought year (2000, 2003–06, 2010–11, and 2016–17), and day of the year. We assessed whether privately or publicly owned wetlands had differing changes as the result of drought and regional differences in open-water probability. For full details of the methods and results for these analyses, see Reiter and others (2018; appendix 1).

Petrie and others (2016) provided initial evidence that drought severely affected irrigation of wetlands and bioenergetics of waterfowl in regions of the Central Valley. Therefore, we hypothesized that a detailed and spatially explicit analysis of the Central Valley (this study) could indicate a reduced probability of irrigation and, ultimately, reduced food biomass available in wetlands for waterfowl and shorebirds. We used the classified irrigated and non-irrigated data for 2000–17 to characterize the probability that a seasonal wetland was irrigated and, specifically, to what extent drought (same year classes as detailed earlier in the text), region, land ownership, and water management priority influenced irrigation rates. We evaluated the differences in proportion of irrigated wetlands and drought impacts between the Central Valley Project Improvement Act (CVPIA) wetlands and the non-CVPIA wetlands and between public and private land. We used a mixed-effect logistic regression to fit seven models to explore factors, and particularly drought, that influence the probability of irrigation. Six models included a factor classifying drought versus non-drought years between 2000 and 2017. For one model, we looked at differences between drought years within 2000–11 and extreme drought years 2013–15. To account for differences in spectral band wavelength ranges and subsequently NDVI values between the sensors, we included a factor in all models that indicated if the base satellite imagery came from Landsat 5 or Landsat 8. We ranked models using Akaike's Information Criterion (AIC; Burnham and Anderson, 2002) to understand the relative influence of different factors, but we also explored the influence of individual covariates based on estimated regression coefficients in each model. Lastly, we evaluated spatial changes in irrigation likelihood during drought by subtracting the probability of irrigation during non-drought years from the probability in drought years (2000–11). All analyses were completed using the lme4 package (Bates and others, 2015) in the statistical software R v3.3.3 (R Core Team, 2018).

Results

Wetland Type

Overall, the heuristic-only model (Base) had lower accuracy than the Base model plus additional covariates of water inundation patterns (that is, Base Plus model) when evaluating six distinct cover types (table B2) or among three cover types (table B3). We had high accuracy in predicting seasonal wetlands across all models (95-percent correct); however, our models did not distinguish well between seasonal and semi-permanent/permanent wetlands, and accuracy was low for semi-permanent/permanent wetlands (17 percent and 19 percent; table B2 and table B3, respectively). When misclassified, semi-permanent/permanent wetlands were mainly classified as seasonal. The Base Plus model included the following parameters: proportion of polygon classified as seasonal wetland based on heuristic; proportion of the polygon classified as semi-permanent/permanent; average proportion of the polygon that was inundated in May or June; average probability of open water in the wetland unit across a calendar year; and whether or not a single pixel was called semi-permanent/permanent in the wetland unit based on the heuristic. The confusion matrix indicated that models likely overestimated the area of seasonal wetlands and underestimated the area of semi-permanent/permanent wetlands (table B3). Other cover types from the data used in the model also were underestimated but generally were accurately classified, particularly when using the Base Plus model (table B3).

Table B2. Confusion matrix for random forest classification models of land cover type (n=6) using data from the Sacramento National Wildlife Refuge Complex (2000–11), California, United States.

[The Base model included only variables derived using the heuristic of Petrik and others (2014), whereas the Base Plus model included variables on the average monthly probability of open water and a factor indicating if even one pixel in the unit was classified as semi-permanent/permanent. **Abbreviations**: For, forest; Oth, other; SP, semi-permanent/permanent wetland; Seas, seasonal wetland; Um, unmanaged wetland; Up, upland; Acc, prediction accuracy; proportion correctly classified]

Cover type	Predicted cover type						
	For	Oth	SP	Seas	Um	Up	Acc
Base model							
For	1	0	0	30	3	0	0.03
Oth	0	0	2	11	0	0	0.00
SP	0	0	42	204	6	1	0.17
Seas	0	0	37	1,561	52	4	0.94
Um	0	0	8	283	98	13	0.24
Up	0	0	4	139	45	14	0.07
Base Plus model							
For	1	0	0	13	14	6	0.03
Oth	0	0	3	7	3	0	0.00
SP	0	0	44	191	17	1	0.17
Seas	1	0	24	1,574	51	4	0.95
Um	2	0	8	76	266	50	0.66
Up	0	0	6	21	121	54	0.27

Table B3. Confusion matrix for random forest classification models of land cover type (n=3) using data from the Sacramento National Wildlife Refuge Complex (2000–11), California, United States.

[The Base model included only variables derived using the heruristic of Petrik and others (2014), whereas the Base Plus model included variables on the average monthly probability of open water and an indicator for if even one pixel in the unit was classified as semi-permanent/permanent. **Abbreviations**: OthP, other plus (other + upland + forest + unmanaged wetland); SP, semi-permanent / permanent wetland; Seas, seasonal wetland; Acc, prediction accuracy]

Cover type	OthP	SP	Sea	Acc
		Base model		
OthP	211	8	432	0.32
SP	17	40	196	0.16
Seas	74	36	1,544	0.93
		Base Plus model		
OthP	533	11	110	0.81
SP	27	49	176	0.19
Seas	72	23	1,542	0.94

Our classification model for irrigated and non-irrigated wetland performed well (Area Under the Curve = 0.88). Our initial model that minimized the difference in sensitivity and specificity to define the threshold for irrigation (Liu and others, 2005) tended to overestimate relative area of wetland irrigation, however. We manually adjusted the NDVI threshold to 0.387 (on a unitless scale from –1 to +1, higher values indicating more or greener vegetation) to better balance the errors, achieve less biased estimates (fig. B1), and to ensure we did not greatly overestimate irrigation. Once we calibrated the threshold of the predicted probability of irrigation, we estimated an overall 84-percent accuracy of predictions. We were slightly more accurate at predicting non-irrigated wetlands (89-percent accuracy) than irrigated wetlands (80-percent accuracy), but we only overestimated irrigation extent by 7 percent (based on our ground validation data, fig. B1). In our classification of predicted irrigation or non-irrigation for each unit of seasonal wetland, the NDVI (in August) had the largest relative influence (53-percent accuracy), and the NDVI in July (34-percent accuracy) and September (13-percent accuracy) had relatively less influence.

For all model classifications, we had enough ground validation data only from the Sacramento National Wildlife Refuge in the northern part of the Central Valley. Consequently, expert review of our maps from the southern part of the Valley highlighted a significant propensity to underestimate the extent of irrigation. Hence, we only used predicted irrigation from the Sacramento Valley for additional analyses. Additional ground validation data on irrigation are needed to reliably extend the model to other parts of the Central Valley.

Drought

Overall, our results suggested that between 2000 and 2011 drought conditions had limited effect on the overall amount of flooding of wetlands, rice, corn, or other suitable agricultural crops (Reiter and others, 2018; appendix 1). However, the 2013–15 drought had a dramatic impact on the total amount of open water in suitable cover types used by waterfowl and shorebirds (30–80-percent declines). The southern Central Valley (San Joaquin Valley) wetlands and corn exhibited larger declines in open water (particularly through the mid-winter) than those suitable cover types in the northern Central Valley, particularly rice (Reiter and others, 2018). Between 2000 and 2017, a model of the probability of seasonal wetland irrigation that included an interaction between the CVPIA wetlands and drought was the best supported (table B4). Drought had a significant negative effect on irrigation in all models (in which it was included). On average, drought years had a 33-percent (95-percent confidence interval [CI]: 30–33 percent) lower probability of irrigation (24 percent) than non-drought years in the Sacramento Valley. During the extreme drought 2013–15, our data suggested that irrigation dropped to 17 percent (95-percent CI: 14–20 percent).

Table B4. Summary of models predicting the probability of irrigation of managed wetland in the Sacramento Valley of California, 2000–17.

[All models included an intercept and a covariate indicating whether the data was from Landsat 8 (2013–17) and models are arranged in order of best performing (lowest ΔAkaike's information criterion [AIC]) to worst performing (highest ΔAIC) model. **Abbrebiations**: LL, log-likelihood; ΔAIC, difference between model AIC and lowest AIC in model set; CVPIA, indicator for wetlands included as part of the Central Valley Project Improvement Act]

Model number	Model	AIC	LL	ΔAIC
4	CVPIA* drought[1]	12,178.82	–6,083.41	0
6	Ownership[2]* drought	12,243.28	–6,115.64	64.46
7	Year type[3]	12,274.60	–6,132.30	95.78
2	Drought	12,291.92	–6,141.96	113.10
3	CVPIA	12,315.26	–6,153.63	136.45
5	Ownership	12,381.83	–6,186.92	203.01
1	Intercept[4]	12,423.36	–6,208.68	244.54

[1]Drought indicates whether the water year was classified as a "drought" or "critical" by the California Department of Water Resources.

[2]Ownership indicates whether the wetland is private or non-private land.

[3]Year type is a three-level factor indicating whether non-drought year (2000, 2003–06, 2010–11, and 2016–17); drought year (2001–02, 2007–09); or extreme drought year (2013–15).

[4]Intercept indicates model included an intercept only along with factor indicating change from Landsat 5 to Landsat 8.

Model parameter estimates revealed that the CVPIA wetlands were less likely to be irrigated than the non-CVPIA wetlands and were significantly more negatively impacted by drought than the non-CVPIA wetlands (table B5). Lastly, private wetlands had significantly higher irrigation rates than public wetlands and were less affected by drought. Based on our intercept-only model, overall average rates of irrigation from all seasonal wetlands across the Sacramento Valley were considerably lower (36 percent; 95-percent CI: 32–41 percent) than those estimated previously for years 1999–2001 during non-drought (56 percent; Naylor, 2002). Mapping the change in irrigation rates as the result of drought across the Sacramento Valley highlighted concentrated declines in irrigated wetlands around the Sutter Buttes (fig. B2) and in smaller wetland complexes further south.

Discussion

Remote sensing is a powerful tool for evaluating and tracking ecological systems. Our work highlights its value for quantifying the impact of drought on quantity and quality of habitats used by waterfowl and shorebirds in the Central Valley of California. Overall flooding duration and extent of managed wetlands were dramatically reduced by extreme drought (2013–15) compared to non-drought years 2000–11, but drought years 2000–11 did not significantly reduce habitat quantity for waterfowl and shorebirds (Reiter and others, 2018).

Open water was reduced in mid-winter, and water in wetlands tended to decrease faster in the late winter and spring of drought years compared to non-drought years. Because extreme droughts like were experienced from 2013 to 2015 could become more frequent in California (Snyder and others, 2004), our results suggested that approaches to prevent the decrease in habitat when faced with water scarcity are needed.

Greenness metrics (NDVI) were effective at distinguishing between irrigated and non-irrigated wetlands in the Sacramento Valley. However, initial predictions to the San Joaquin Valley detected almost zero irrigation, which we knew was incorrect. These results indicated that greenness phenology could be different across the Central Valley, which likely is due to the differences in the timing of peak greenness in wetland plants such as between swamp timothy (*Crypsis schoenoides*) and watergrass (*Echinochloa crusgalli*). Swamp timothy is relatively more dominant than watergrass in the San Joaquin, whereas watergrass is relatively more dominant than swamp timothy in the Sacramento Valley. However, when using only data from the Sacramento Valley, we estimated a much lower rate of irrigation (36 percent) compared to the irrigation rate of 56 percent derived by Naylor (2002) and used in the Central Valley Joint Venture Implementation Plan (Central Valley Joint Venture, 2006).

Table B5. Summary of coefficient values for all models fit to estimate probability of irrigation of seasonal wetlands (2000–17) and to assess the influence of drought, landownership, and water priority and location on irrigation in the Sacramento Valley of California.

[Model estimates correspond by model number with models in table B4. **Abbreviations**: SE, standard error; %, percent; CI, confidence interval; CVPIA, Central Valley Project Improvement Act]

Covariate	Estimate	SE	P-value	95% CI low	95% CI upper
Model number 1					
Intercept[1]	–0.82	0.09	0.00	–1.01	–0.64
Landsat[2]	2.03	0.06	0.00	1.91	2.14
Model number 2					
Intercept	–0.57	0.10	0.00	–0.76	–0.38
Drought[3]	–0.58	0.05	0.00	–0.67	–0.48
Landsat	2.14	0.06	0.00	2.02	2.26
Model number 3					
Intercept	0.02	0.11	0.88	–0.21	0.24
CVPIA[4]	–1.85	0.17	0.00	–2.18	–1.51
Landsat	2.02	0.06	0.00	1.91	2.14
Model number 4					
Intercept	0.22	0.12	0.07	–0.02	0.45
CVPIA	–1.75	0.18	0.00	–2.10	–1.39
Drought	–0.46	0.07	0.00	–0.59	–0.33
Landsat	2.14	0.06	0.00	2.03	2.26
CVPIA* drought	–0.26	0.10	0.01	–0.45	–0.07
Model number 5					
Intercept	–1.27	0.11	0.00	–1.50	–1.05
Ownership[5]	1.24	0.18	0.00	0.87	1.60
Landsat	2.03	0.06	0.00	1.91	2.14
Model number 6					
Intercept	–0.97	0.12	0.00	–1.21	–0.74
Ownership	1.10	0.19	0.00	0.72	1.48
Drought	–0.69	0.06	0.00	–0.82	–0.57
Landsat	2.15	0.06	0.00	2.03	2.27
Ownership* drought	0.31	0.10	0.00	0.11	0.51
Model number 7					
Intercept	–0.64	0.10	0.00	–0.83	–0.45
2000–11 drought	–0.44	0.06	0.00	–0.56	–0.33
2013–15 drought	–0.94	0.09	0.00	–1.12	–0.75

[1]Intercept represents non-drought in all models.

[2]Landsat indicates variable of whether from Landsat 8 (1) or Landsat 5 (0).

[3]Drought indicates variable of whether in a drought year.

[4]CVPIA indicates variable of whether the wetland unit was a Central Valley Project Improvement Act wetland.

[5]Ownership indicates variable of whether the wetland unit was privately owned.

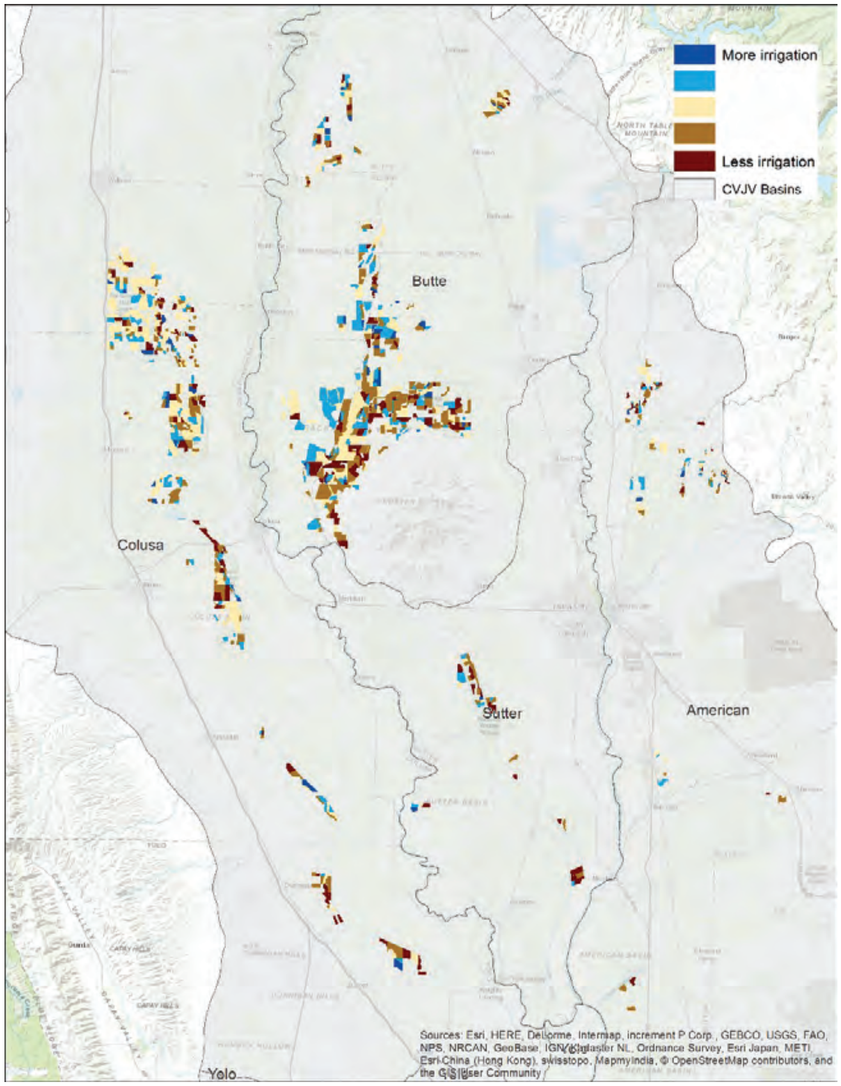

Figure B2. The difference in probability of irrigation between drought (2001–02, 2007–09) and non-drought years (2000, 2003–06, 2010–11) in the Sacramento Valley of California, 2000–11. "More irrigation" indicates higher probability of irrigation in drought years.

Though, our irrigation rate was higher than that estimated from the ground validation data for the Sacramento National Wildlife Refuge Complex that were used to build and test the model; the complex averaged an irrigation rate of 22 percent of seasonal wetland marsh units receiving irrigation for 2000–15. Ultimately, more ground validation data are needed from across the Central Valley to improve the accuracy of this classification model for all wetlands.

In addition to reducing habitat quantity (Reiter and others, 2018), drought had a significant negative impact on habitat quality. Irrigation rates were significantly lower in drought years compared to non-drought years during 2000–17. This was not surprising because when water availability is reduced, wetland managers can forego irrigation and still produce food for waterfowl, albeit 50 percent less than if irrigated (Naylor, 2002). Our estimates of irrigation rates during all drought years between 2000 and 2017 (17 percent [extreme drought] and 24 percent [average drought]) were higher than those presumed by Petrie and others (2016) in extreme drought that were derived by expert opinion (10 percent).

Our remote sensing classification approach for distinguishing between seasonal, semi-permanent, and permanent wetlands using the water-inundation heuristic, which sought to replicate the work of Petrik and others (2014), was not particularly effective. In part, we found that cloud cover in January limited the amount of data available for classification models across years. Petrik and others (2014) completed their analysis on 2009 imagery that had cloud-free data for January and June. As we attributed our data to develop and test the model-based heuristic, we realized that in many years there were too much cloud cover to obtain the needed data. Even when we modified the heuristic to allow water in December to also indicate a seasonal wetland, we still found a lot of missing data. Future efforts that use remote classification models for this region may wish to consider strategies to account for cloud cover.

Additional covariates that represented the full annual pattern of water improved model accuracy for delineating wetlands but still did not accurately identify types of managed wetlands, although we predicted seasonal wetland very accurately. However, the inclusion of water metrics did help our model differentiate quite well between managed wetlands and other cover types. This remote sensing model can help to define the managed wetland footprint in the Central Valley. More refined and managed wetland vegetation maps, including individual moist soil seed plant species and productivity, are available (Lorenz and Byrd, 2018). However, our models of managed wetland and irrigation rates, when integrated with Water Tracker (an automated open surface water tracking system; see chapter D), can serve to quantify the extent of management and quickly highlight year-to-year variation in habitat quality because these classifications are largely built on spatial data products (regarding the distribution of water) that are being generated every 16 days (www.pointblue.org/watertracker). We consider non-irrigated wetlands to be of lower quality because they have been shown to have half of the food availability when compared to irrigated wetlands (Naylor, 2002).

Our findings that the CVPIA wetlands had lower irrigation rates than the non-CVPIA wetlands and that private land had higher irrigation rates than public land, are likely related. It could be that most privately managed wetlands are associated with waterfowl hunting clubs, and thus, there is the sole emphasis on maintaining the highest quality wetlands for waterfowl. By providing extensive summer irrigations, the private wetlands can boost habitat quality (in other words, wetland seed abundance and biomass) for waterfowl (Naylor, 2002). Additionally, private land could be limited by how much water they can afford to purchase or pump, whereas the CVPIA wetlands are mainly reliant on their designated allocation of water and have more limited opportunities to increase water supply. Other analyses we have completed suggested that the amount of open-water wetland habitat in the CVPIA wetlands is positively associated with their annual water allocation, which is not fixed but is partly driven by drought (Reiter and Jongsomjit, 2019).

In the highly managed hydrological landscape of the Central Valley, drought can still have a substantial impact on the quantity and quality of wetland habitats for waterfowl and shorebirds. Both managed wetlands and flooded agriculture declined during 2013–15. However, our analyses suggested that habitat quality could be more sensitive to regular drought than flooding duration and extent. Both the recent extreme drought (2013–15) and drought years 2000–11 (generally less severe) had a significant negative impact on irrigation rates; however, only the extreme drought years resulted in a significant change in the magnitude and duration of inundated wetlands (Reiter and others, 2018). Although the impact on waterbirds is not completely understood (Petrie and others, 2016; and chapter C), finding strategies to maintain irrigation of wetlands, thus boosting their quality during drought, particularly extreme drought, could be able to offset losses of waterfowl habitat due to reduced flooding of managed wetlands and agriculture. Our model of irrigation rates can be generated annually by the time managers that are considering flooding their wetlands in the fall (October) because it uses satellite imagery from July–September. Providing those data to managers and conservation planners that are depending on extent of summer irrigation can offer guidance regarding the overall state of managed wetland seed resources and hopefully inform decisions on the quantity of habitat to create (see chapter D).

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Chapter C. Objective 2: Evaluate the Impact of Changes in Waterfowl and Shorebird Food Energy Supplies

By Matthew Reiter and Dennis Jongsomjit

Introduction

Drought influences the amount of water available for wetland management in the Central Valley. Particularly, seasonal wetland irrigations (see chapter B) and the total extent flooded are reduced (Reiter and others, 2018). The amount of planted wildlife suitable crops and post-harvest flooding of those crops is reduced as well (Petrie and others, 2016; Reiter and others, 2018). For conservation planning in the Central Valley, the Central Valley Joint Venture (CVJV) relies on bioenergetics models to assess habitat needs to meet current waterfowl and shorebird populations and desired population objectives (Central Valley Joint Venture, 2006; Petrie and others, 2016; Dybala and others, 2017). To understand the impact of drought on shorebirds and waterfowl, particularly from changes in habitat quantity and quality, we used a bioenergetics modeling approach with empirically derived parameters to estimate energy deficits under different scenarios of drought for the full CVJV planning region (except for Suisun Marsh because we did not have reliable wetland food availability data).

Methods

We adopted the TRUEMET avian bioenergetics model (previously used by the CVJV) to support conservation planning for Valley non-breeding waterfowl (Petrie and others, 2016). We also used a similar model inspired by TRUEMET for shorebirds (Dybala and others, 2017). Hereafter, these two models will be referred to as bioenergetics models or models. We used these models to analyze scenarios of drought versus non-drought and with varying waterfowl and shorebird population sizes. The models allowed us to translate scenario habitat conditions and levels of waterfowl and shorebird food demand in the Valley to deficits in bird food supplies (kcal) and days of food energy deficit. The models calculate and compare the food energy supply provided under a given set of scenario habitat conditions with the food energy demand required to support wintering and migrating waterfowl and shorebirds assuming a defined bird population size (assuming population objectives are achieved; Pearse and Stafford, 2014; Williams and others, 2014). Deficits of food supplies can be assessed on 15-day intervals for waterfowl and 1-day intervals for shorebirds, which allowed determination of seasonal variation in deficits for each scenario.

In bioenergetics models, food energy available for waterfowl was based on estimated seed production in each crop and wetland habitat type and invertebrate biomass in seasonal wetland during January–March when invertebrate consumption is relatively high (Petrie and others, 2016). Modeled food energy for shorebirds was based on estimated biomass of invertebrates in each habitat type (Dybala and others, 2017). We combined our estimates of available open-water habitat and summer-irrigated wetland developed from our Landsat-derived open-water datasets with literature-based information of habitat food resources in models (table C1; Petrie and others, 2016; Dybala and others, 2017). Because of differences in foraging ecology of ducks and geese, modeling accounted for differences in duck and goose habitats and availability of respective food supplies in estimating overall waterfowl food deficits and deficit days; by contrast, shorebirds are more similar in their use of habitats and their available food and could be modeled as one group. The waterfowl and shorebird population objectives included in our analysis were established by the CVJV (Dybala and others, 2017; Central Valley Joint Venture, unpub. data, 2020). The conservation objective population size for non-breeding waterfowl in the Valley was based on the North American Waterfowl Management Plan's goals for waterfowl on continental breeding areas that was stepped-down to Joint Venture regions (for example, Central Valley; Central Valley Joint Venture, unpub. data, 2020). Shorebird population objectives equated to double the shorebird population size baseline estimated from years 1992–95 (Dybala and others, 2017).

Table C1. Summary of parameter estimates and sources used to assess the effects of extreme drought (2013–2015) compared to long-term average conditions (2000–2017) on bioenergetics models for shorebirds and waterfowl in the Central Valley of California.

[Parameter values that are not in the table were defined previously in models for shorebirds (Dybala and others, 2017) and waterfowl (Petrie and others, 2016), or were based on a continuous range of modeled values in Reiter and others (2018). **Abbrevations**: <, less than; NA, not applicable; %, percent; cm, centimeter]

Parameters	Shorebirds		Waterfowl	
	Average	Drought	Average	Drought
Total base hectares seasonal wetland	67,652	67,652	67,652	67,652
Total base hectares semi-permanent wetland	6,908	6,908	NA	NA
Total base hectares rice	223,854 (2007–12)	169,606 (2014)	223,854	169,606
Total base hectares corn	108,443 (2007–12)	90,215 (2014)	27,111	22,554
Total base hectares other crops	860,942 (2007–12)	524,644 (2014)	NA	NA
Proportion of suitable cover type open water (<30% vegetated)[1]	Modeled daily area flooded by habitat type	Modeled daily area flooded by habitat type	Modeled daily area flooded by habitat type	Modeled daily area flooded by habitat type
Proportion irrigated	NA	NA	0.36 [2](0.56)	0.24 [3](0.17)
Proportion suitable depth[4]	Predicted daily proportion of flooded area <10 cm deep	Predicted daily proportion of flooded area <10 cm deep	NA	NA

[1]Proportion of suitable cover type open water from Reiter and others (2018).

[2]Proportion irrigated from Naylor (2002).

[3]Proportion irrigated in extreme drought.

[4]Estimated as the proportion of the open-water area that is accessible to shorebirds (in other words, <10 cm) from Dybala and others (2017).

In our analysis, we assessed bioenergetics for the CVJV conservation planning periods for migrating and non-breeding waterfowl and shorebirds, respectively, August 15–March 31 (211 days) and July 1–May 15 (319 days; Central Valley Joint Venture, 2006). These models use several parameters to determine the total energy available on the landscape, including the total flooded area of seasonal and semi-permanent wetlands, post-harvest rice, post-harvest corn, and post-harvest field and row crops. We derived flooding curve parameters (proportion of each cover type that is flooded on each day) for bioenergetics models from the classified wetland data described in chapter B to assess the impact of changing wetland availability as the result of drought on meeting waterfowl and shorebird population objectives (Reiter and others, 2018). We considered four curves specific for drought and non-drought years from 2000 to 2011, extreme drought years from 2013 to 2015, and the average across 2000–15 (Reiter and others, 2018). The waterfowl bioenergetics model allowed food energy to vary depending on the proportion of irrigated and non-irrigated seasonal wetlands. Previous research estimated that moist soil seed biomass was reduced by 50 percent when seasonal wetlands were not irrigated and estimated that, on average, 56 percent of seasonal wetlands were irrigated (Naylor, 2002). We used our estimates of the probability of a managed wetland being irrigated in drought versus non-drought years to better understand the overall drought impact on waterfowl bioenergetics. We considered four irrigation rate parameters: (1) the 2000–17 modeled average from classified maps detailed in chapter B; (2) the average during drought years 2000–11; (3) the value used by the Central Valley Joint Venture (2006) and Petrie and others (2016) for non-drought, which is higher than (1) or (2); and (4) the average from extreme drought years 2013–15 (table C1). All irrigation parameters were larger than the assumption of 10-percent irrigation derived from conversations with wetland managers used to assess the recent drought by Petrie and others (2016). Because we did not have data on variation in water depth as the result of drought, a key parameter defining habitat accessibility for shorebirds, we considered the depth ratio parameter (the proportion of flooded habitat that is of suitable shorebird depth) to be the same in all scenarios evaluated.

We evaluated two sets of population sizes for non-breeding shorebirds and waterfowl. For shorebirds, we followed Dybala and others (2017) and considered current population objectives derived from Shuford and others (1998) that were a minimum of 50,000 mean of 207,991 and maximum of 333,370 shorebirds. Long-term (100-year) objectives that were two-times larger than the currently estimated populations were a minimum of 50,000 mean of 322,771 and maximum of 600,000 shorebirds. For waterfowl, we used population objectives recently developed by Central Valley Joint Venture (unpub. data, 2020) that are downscaled from Fleming and others (2018) for the update of the CVJV implementation plan. The "current" objectives for waterfowl are based on the long-term average (LTA; years 1998–2014), and the aspirational (or 100-year) goal is based on the 80th percentile of the LTA. We summarized the effect of the different scenarios based on the total number of days with a deficit in food energy across the planning window and compared the effect of changes in scenarios between waterfowl and shorebirds based on the proportion of planning days that were in energy deficit to account for different planning window durations.

Results

Both shorebirds and waterfowl exhibited energy shortfalls under all scenarios evaluated with bioenergetics models. At current population sizes, both shorebirds and waterfowl have a similar number of deficit days for non-drought during 2000–11, drought during 2000–11, and LTA conditions (table C2). By contrast, extreme drought more than doubled deficit days for shorebirds, and increased the waterfowl deficit by 18–25 days (46–78 percent) relative to other year types assuming current population objectives (table C2). At current population objectives, deficit days in drought years from 2000 to 2011 were different only by 1–2 days compared to non-drought years from 2000 to 2011 and LTA for both waterfowl and shorebirds. At 100-year population objectives, deficit days in drought years versus non-drought years in 2000–11 and LTA were also limited (5–7 days) for shorebirds and waterfowl. However, extreme drought resulted in 43–58 percent increases in deficit days for waterfowl and approximately 200-percent increases for shorebirds relative to other year classes assuming the 100-year population objectives. When comparing populations at current versus 100-year objectives, shorebirds showed a very large increase in deficit days across all categories: from 36 to 92 days during non-drought, 37 up to 99 days during drought, 37 up to 94 days for LTA, and 78 up to 293 deficit days during extreme drought, respectively (table C2).

Table C2. Total number of deficit days (percentage of planning days) derived from bioenergetics models for wintering shorebirds and waterfowl under different scenarios of drought in the Central Valley of California, United States, between 2000 and 2017.

[%, percent; LTA, long-term average; CVJV, Central Valley Joint Venture]

Year type[1]	Deficit days
Shorebirds, current population	
Non-drought	36 (11%)
Drought	37 (12%)
Extreme drought	78 (24%)
LTA	37 (12%)
Shorebirds, 100-year population	
Non-drought	92 (29%)
Drought	99 (31%)
Extreme drought	293 (92%)
LTA	94 (29%)
Waterfowl, current population	
Non-drought	38 (18%)
Drought	39 (18%)
Extreme drought	57 (27%)
LTA	39 (18%)
LTA-CVJV[2]	32 (15%)
Waterfowl, 100-year population	
Non-drought	55 (26%)
Drought	55 (26%)
Extreme drought	79 (37%)
LTA	55 (26%)
LTA-CVJV[2]	50 (23%)

[1]Year type is a four-level factor indicating whether non-drought year (2000, 2003–06, 2010–11, and 2016–17); drought year (2001–02, 2007– 09); or extreme drought year (2013–15); LTA equals long-term average scenario (2000–17).

[2]Assumes 56 percent of seasonal wetlands are irrigated versus 36 percent in LTA scenario.

Waterfowl deficit days increased relative to current waterfowl population objectives by 38–56 percent because of a relatively larger energy demand from waterfowl populations under the 100-year objectives. However, because the planning windows are different lengths, the percentage of the planning window that was in deficit revealed differences among the guilds. At current populations, waterfowl had a higher percentage of deficit days with respect to planning window duration than shorebirds (20 percent versus 15 percent, respectively). However, at 100-year objectives, this pattern was reversed with a much higher percentage of the shorebird planning interval days being in energy deficit (45 percent) compared to waterfowl (29 percent). A large driver of this difference was the impact of extreme drought on deficit days for shorebirds at 100-year objectives (92 percent of planning days were in deficit). Considering the irrigation rate from Central Valley Joint Venture (2006) of 56 percent when evaluating the LTA scenario rather than our 36 percent derived for Sacramento Valley (that is, scenario "LTA-CVJV" versus "LTA"), there were reductions in deficit days for waterfowl from 39 to 32 days under current populations and 55 to 50 days for long-term population objectives (table C2).

The timing of deficits varied between shorebirds and waterfowl (fig. C1). Under all scenarios, waterfowl deficits occurred in winter (January–March) and shorebirds deficits occurred in the summer (July–September) and then again in the late winter and spring (March–April). Deficits in the spring for shorebirds were evident under extreme drought conditions at current populations and under all scenarios when considering 100-year population objectives.

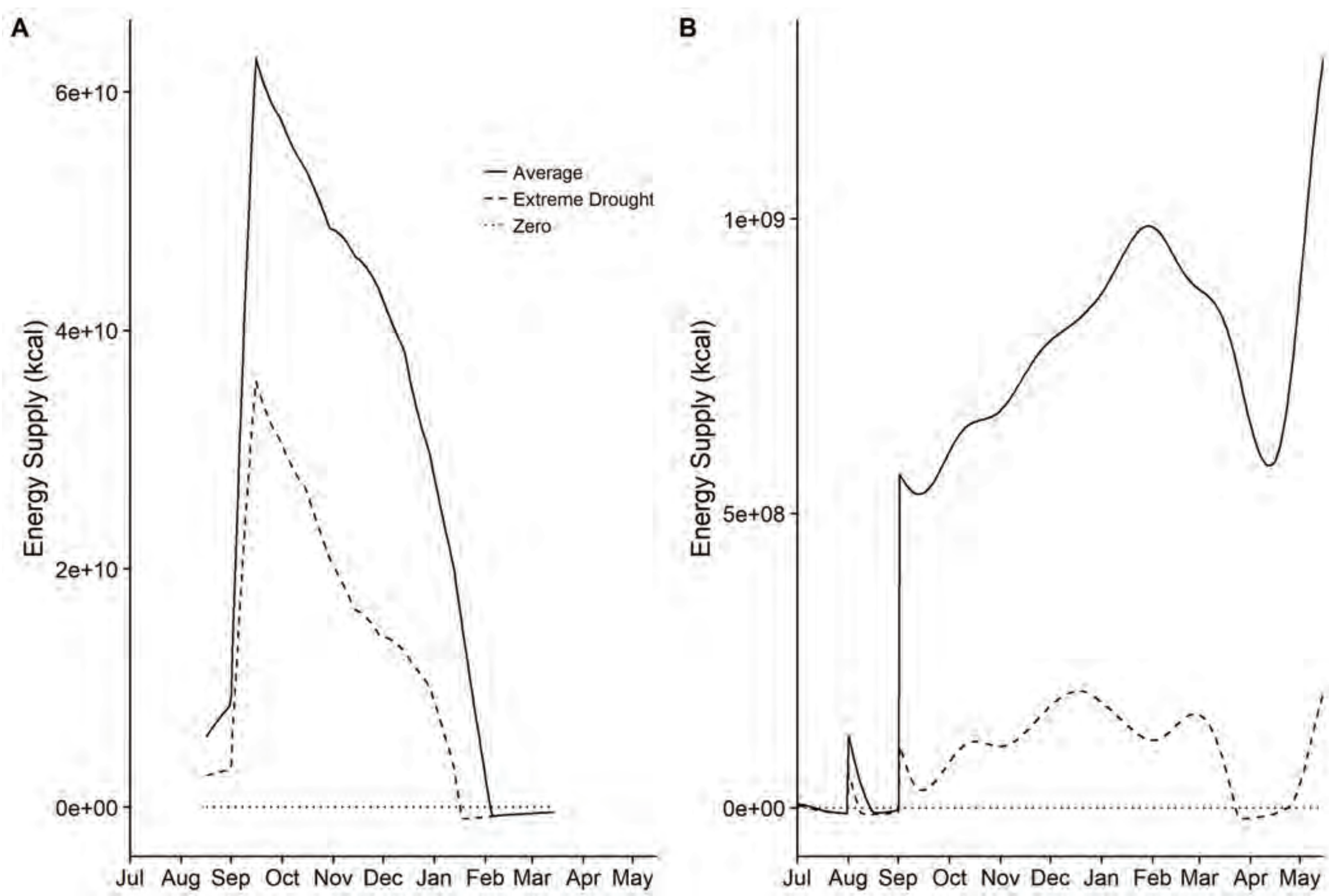

Figure C1. Summary of energy supply (kilocalorie; kcal) available when accounting for *A,* waterfowl; and *B*, shorebird populations at current population levels and assessing average conditions (solid line; years 2000–17) and extreme drought conditions (dashed line; years 2013–15). When energy supply is below the zero (dotted) line there is a deficit day.

Discussion

Although our previous assessment of the impact of drought highlighted dramatic changes in the availability of habitat used by waterfowl and shorebirds (Reiter and others, 2018; chapter B of this report), our ability to understand the effect on the birds that rely on those habitats was limited. By evaluating changes in waterfowl and shorebird habitat quality and quantity from a bioenergetics perspective, we were better able to assess the impacts on the birds. Although Petrie and others (2016) considered similar scenarios of drought, their analyses relied on expert opinion to characterize changes in parameters as the result of drought. In contrast, we sought to generate empirically derived parameters.

Extreme drought (2013–15) substantially increased deficit days for shorebirds and waterfowl whereas droughts between 2000 and 2011 did not. These findings were consistent with the differences in drought impact on habitat detailed by Reiter and others (2018). Our analyses, like other studies, indicated that waterfowl experienced energy deficits in winter (as early as mid-January) during drought (Petrie and others, 2016), but shorebirds experienced energy short-falls in late summer and early fall (Dybala and others, 2017) as well as in spring at population objectives. However, our results for average conditions suggested deficits for waterfowl could start as early as mid-February, whereas Petrie and others (2016) indicated deficits beginning in March. The cause of this difference may be related to our removal of the Suisun planning basin from the analysis. Although we also removed the associated waterfowl population objectives (shorebird objective already did not include Suisun [Dybala and others, 2017]), Suisun is one of the nine planning basins considered by the CVJV with a consistent surplus of energy in winter (Central Valley Joint Venture, 2006). The removal of the nearly 15,000 hectares of seasonal wetland in Suisun from the bioenergetics model and its associated surplus of food for its population objectives likely accounts for the differences observed.

Our data suggest that for shorebirds, targeting the fall for habitat creation and enhancement is good in drought and non-drought years, and that providing additional suitable wetland habitat in the spring is essential during drought years. For waterfowl, late winter is the preferred time for providing additional habitat. These assessments of food energy gaps are helping The Nature Conservancy to effectively target their dynamic conservation actions in the Sacramento Valley (Reynolds and others, 2017). Their BirdReturns program seeks to provide habitat from August–October and February–April to fill the food energy supply shortfalls detected with our analysis. Some of the highest densities of waterfowl (Sesser and others, 2018) and shorebirds (Golet and others, 2018) were observed in flooded rice fields in February and March when flooded rice in the Valley is being drained or is unavailable, respectively, corroborating the bioenergetics model and highlighting the habitat need. The shorebird counts were from drought years and further supported our findings that the need is particularly high in the spring for shorebirds during extreme drought.

Estimates of the proportion of seasonal wetlands that were irrigated, used in our scenarios of average conditions, were lower than those used in other bioenergetics assessments for waterfowl in the Central Valley (Central Valley Joint Venture, 2006; Petrie and others, 2016); however, our data were based on remote sensing of the Sacramento Valley. There were relatively small changes in our findings when assessing the sensitivity of our results to variation in the irrigation rate. When reducing the assumed irrigation rate from 56 percent (Petrie and others, 2016) to 36 percent (chapter B), we found increases in deficit days of only 5–7 days. Although those changes are important, they are smaller than the changes in deficit days related to flooding duration and planted crops that occurs during extreme drought and which resulted in about 40-percent (15–20 days) increases in the number of deficit days.

Our evaluation of the impact of drought on shorebirds was the first of its kind. Our assessment was limited by using a single food accessibility parameter in all bioenergetics models–the proportion of open-water habitat that is of suitable shorebird depth (less than 10 centimeters; Dybala and others, 2017) at different points in the planning window. We could envision water-management actions during drought that could result in both increases in the proportion of accessible habitat (for example, flooding the same wetland extent, but shallower) and decreases in the proportion of accessible habitat (for example, flooding fewer wetlands with deeper water to last the entire season). Hence, we elected to use a previously published accessibility parameter from Dybala and others (2017) and maintain a constant value across scenarios. However, recently published work (Schaffer-Smith and others, 2018) highlighted that the proportion assumed to be accessible to shorebirds in the spring, in managed seasonal wetlands by Dybala and others (2017), was likely overestimated. These analyses generated depth ratio (proportion suitable depth) data through a combination of satellite imagery and high-resolution bathymetry. Sensors used by Schaffer-Smith and others (2018) collected additional data from 2014 to 2018, so future analyses can better define the average proportion of accessible habitat and assess how varying the depth ratio parameter for drought years and flood years impacts shorebirds.

To better manage wetlands for waterfowl and shorebirds requires understanding the timing and magnitude of habitat needed during drought and non-drought years. Our approach to modeling the impacts of drought on waterfowl and shorebirds using bioenergetics highlights key points in time that we consider to be focal periods of habitat restoration and enhancement. By analyzing bioenergetics, we can assess the full impact of habitat changes on birds that result from extreme drought. This information then can be applied to adjust management strategies as needed when faced with future extreme droughts that are projected to be more frequent in the coming century (Snyder and others, 2004).

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Chapter D. Objective 3: Integrate Wetland Classification Heuristic with Automated Water Tracking Data to Inform and Evaluate Water Allocation Decisions

By Matthew Reiter and Dennis Jongsomjit

Introduction

Management of water and wetlands can be enhanced by understanding how much water and habitat is on the landscape at different points in time. During the 2013–15 drought, wetland managers in the Central Valley requested that more effort be placed on synthesizing habitat availability in near real-time so managers could be more strategic in their use of water. Integration of the Water Tracker and wetland heuristic has enabled rapid assessments of the impacts of drought, flood, and water-management decisions on wetlands and waterfowl and shorebird habitat.

Water Tracker: Online Automated Water Tracking Application

Point Blue Conservation Science, the U.S. Fish and Wildlife Service (USFWS) Inventory and Monitoring Program, and The Nature Conservancy developed and launched the Water Tracker system to facilitate ease of access to open-water datasets (Reiter and others, 2015, 2018; www.pointblue.org/watertracker). Water Tracker provides open-source spatial data on open water and automated data summaries every 16 days (fig. D1). This information is easily accessible and initial summaries can be extracted. To provide this functionality, Water Tracker was developed as an automated system capable of downloading Landsat 8 satellite imagery as soon as it is made available. It processes the imagery using an existing open-water classification model (Reiter and others, 2015, 2018). The classification model has high predictive accuracy (Area Under the Curve greater than 0.9), and Water Tracker also generates an image quality metadata file to track the overall quality of each classified scene. Once processed, approximately 7–14 days post-image acquisition, the open-water data are available for download, visualization, and summary for custom regions of the Central Valley.

Integration of Water Tracker Data with Wetland Classification Heuristic

To take advantage of the science completed as part of this project and to provide findings to those who can use them to improve management and conservation decisions, we integrated the wetland classification model with open-water data to delineate irrigated versus non-irrigated wetlands into Water Tracker (see chapter B). This was easily done because the Water Tracker's open-water classification model used (and currently uses) the Normalized Difference Vegetation Index (NDVI) to mask some areas. Combined with the open-water data, we used the NDVI images for July–September (stored by Water Tracker) to generate predictions of seasonal wetland irrigation. Due to the limitations of our model, we only generated spatial predictions of irrigation for the Sacramento Valley (see chapter B). As part of this project (in Reiter and others [2018], and chapter B), we used Water Tracker data of calculated probability for open water by wetland and crop type in each 2-week interval of classified water data (fig. D1).

Water Tracker Applications for Habitat Management

Water Tracker provided estimates of the proportion flooded of each wetland type that can be readily used to estimate input data for food energy available in shorebird and waterfowl bioenergetics models presented in Dybala and others (2017) and Petrie and others (2016). In chapter C, we used Water Tracker data to calculate available food energy estimates under different year types reflecting differing habitat availability and conditions for the Central Valley.

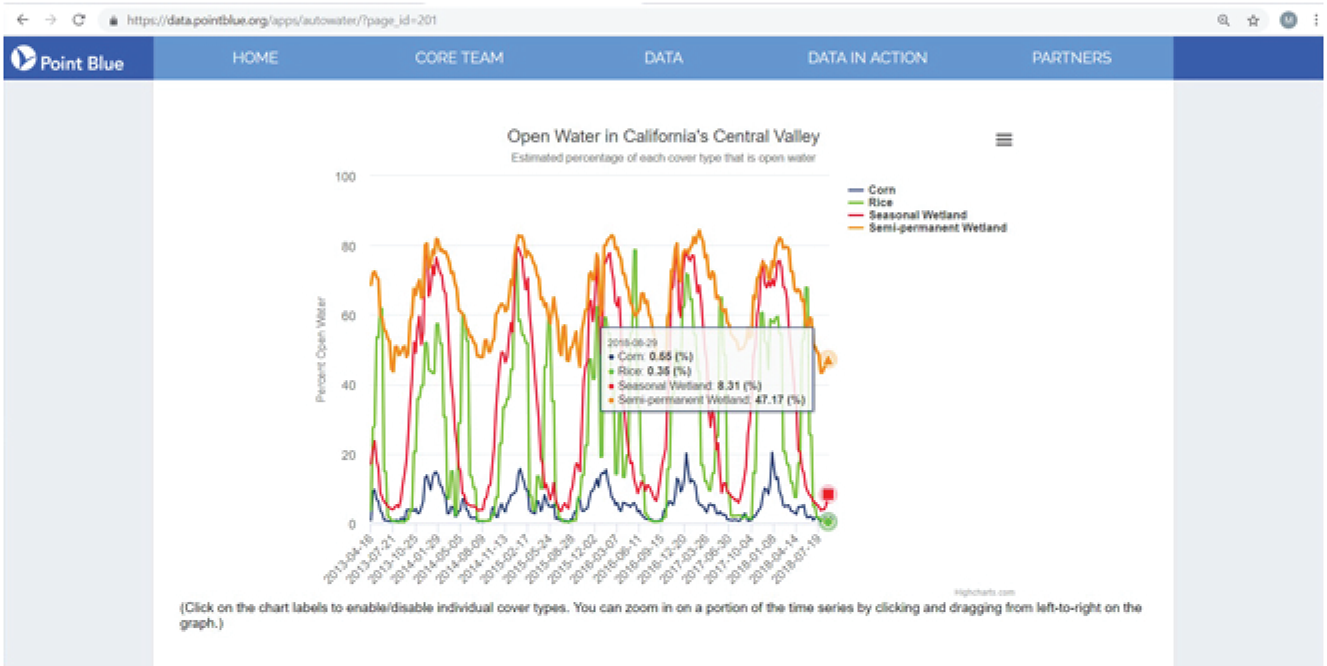

Figure D1. Interactive near real-time time series of the proportion of open water by cover types in the Central Valley of California (on Water Tracker, www.pointblue.org/watertracker).

Suisun Marsh was not included in analysis due to limited understanding of the food availability for waterfowl and shorebirds in this region. We included food energy estimates for different year types as input data in separate scenarios for bioenergetics models. This integration of water tracking, wetland classification heuristic to distinguish seasonal wetlands that are summer-irrigated versus not, and bioenergetics modeling, should provide habitat managers with more refined estimates of food availability under current management designed to promote growth of moist soil seed plants. However, we are still refining how best to account for food consumption in these near real-time estimates. Our current approach assumes that the current distributions and population sizes of shorebirds and waterfowl in the Central Valley are equivalent to those specified by Dybala and others (2017) and Central Valley Joint Venture (unpub. data, 2020), respectively. Future advances in tracking (see chapter E) and estimating waterfowl population sizes in the Central Valley could help refine overall estimates of food shortages and their spatial distribution. Overall, this integration of the Water Tracker, wetland heuristic, and bioenergetics models has enabled rapid assessments of the impacts of drought, flood, and water-management decisions on wetlands, waterfowl and shorebird habitat, and waterfowl and shorebird populations.

Ongoing Development of Water Tracker

Over the course of this project, a complementary project was initiated (April 2017–present) through the support of NASA's Ecological Forecasting Program—"Integrating Remote-Sensing and Ecological Forecasting into Decision-Support for Wetland Wildlife Management and Ecosystem Services in the Central Valley of California: Optimizing Across Multiple Benefits" (http://climate.calcommons.org/forecasting-central-valley-water). These leveraged funds helped to further develop the wetland spatial data products and the analytical capacity of Water Tracker. Data layers representing moist-soil seed wetland plant species, wetland plant productivity, and estimates of wetland plant seed biomass, that will particularly help with waterfowl management, are being integrated into Water Tracker as well as the needed classification models to generate those data annually.

Lastly, to help establish the needed functionality and to train and get feedback on Water Tracker, we held nine information, feedback, and training workshops with potential users of Water Tracker (2016–18). In total, we engaged with more than 50 potential end-users from 10 state and federal agencies and non-governmental organizations representing management of more than 10 state, federal, and private wetland complexes. These sessions helped to improve Water Tracker and ensure the data we generated are useful. With leveraged funds, we will continue to do training and outreach to enhance the value and use of Water Tracker for wetland management decisions.

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Chapter E. Objective 4: Integrate Waterfowl Location and Dynamic Water Data to Evaluate Waterfowl Response to Distribution of Water

By Elliott L. Matchett, Cory T. Overton, and Michael L. Casazza

Introduction

Translating dynamic open-water maps to waterfowl-relevant habitat maps provides a major improvement for wildlife researchers and managers to assist in their assessments of the areas and habitats used by waterfowl as hydrologic conditions change, both temporally and spatially. Suitable habitat maps developed using dynamic water data should accurately and consistently characterize those flooded habitats used by ducks. Because ducks prefer flooded habitats like wetlands and rice fields, duck locations recorded with telemetry technology can be used to validate and enhance maps developed to characterize waterfowl habitats that change temporally with drought or water management. Telemetry data also can be analyzed to infer duck response to drought in terms of distance traveled to feed and overlap in use of space or habitats by ducks, which have implications for the population dynamics of ducks.

Objectives

We investigated the integrated use of Point Blue's Water Tracker maps (in other words, dynamic water data) and duck telemetry data (fig. E1) to evaluate the best use of open-water characteristics in developing a biologically relevant habitat map for waterfowl. The purpose of this objective was to enable analysis of duck space use under spatially and temporally changing hydrologic conditions during periods of drought and non-drought, and seasonally within years. Secondly, we used information about duck locations and space use by ducks to infer potential ecological costs of drought to ducks including, but not limited to, changes in food energy supply and energetic costs.

Methods

Integrating duck location data and water maps involved two efforts: (1) translating the map of water occurrence into a biologically relevant map of waterfowl habitat and (2) analyzing waterfowl space-use patterns as a function of spatial and temporal changes in this habitat map. Evaluating the habitat map accuracy was accomplished using a robust telemetry dataset for ducks (n=66,588 locations from 9 species) marked with frequent, high-resolution (typically less than 5-meters [m] accuracy) Global Positioning System (GPS) transmitters. Duck locations were represented by seven dabbling and two diving species. The dabbling ducks were the American wigeon (*Mareca americana*), blue-winged teal (*Spatula discors*), cinnamon teal (*S. cyanoptera*), gadwall (*M. strepera*), mallard (*Anas platyrhynchos*), northern pintail (*A. acuta*), and northern shoveler (*S. clypeata*). The diving ducks were the canvasback (*Aythya valisineria*) and greater scaup (*A. marila*).

We developed a data processing framework for translating dynamic open-water data to a waterfowl habitat map using our frequent and high-resolution telemetry data for ducks. Telemetry data was used to evaluate alternative processing steps for habitat map development. We assessed two interim map products which guided our development of additional processing steps to develop a final waterfowl habitat map. Map assessments were made using telemetry locations of ducks as indicators of appropriate habitat (correct assignments). The map also was assessed for incorrect classification of habitat due to improper approaches to habitat translation. This assessment was based on the extent and change in the amount of the landscape classified as waterfowl habitat. The data supporting these analyses are available as a U.S. Geological Survey data release (Matchett and others, 2021).

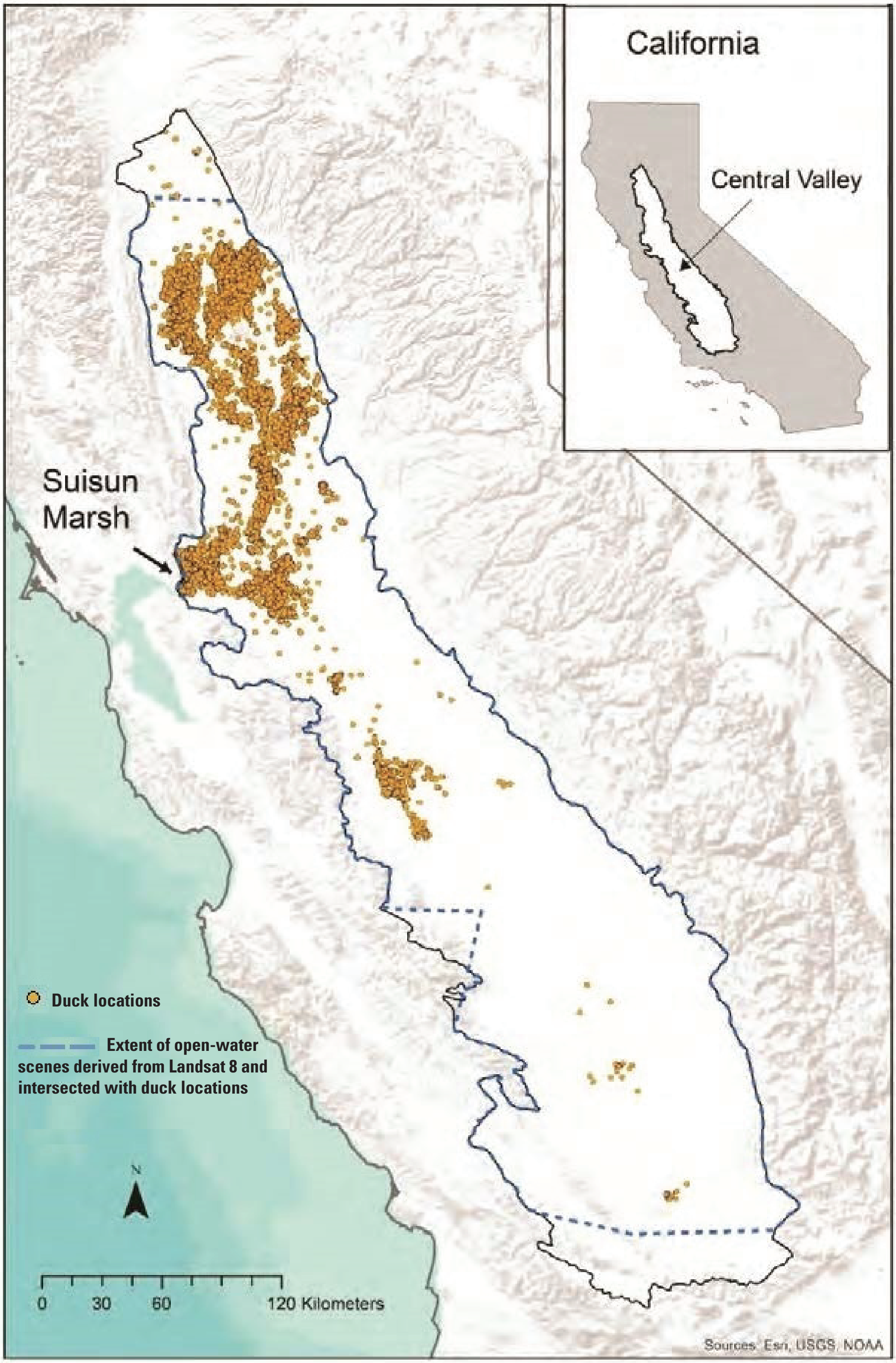

Figure E1. Locations for 387 ducks of 9 species using habitats in the Central Valley and Suisun Marsh in California during fall–winter (October 1–March 31 of the following year). Ducks were marked with Global Positioning System (GPS) transmitters and then released in the Suisun Marsh (primarily), Central Valley, and other locations in the western U.S. during January–March, April–July of years 2015–18.

Collection of Duck Location (Telemetry) Data

Beginning mid-January 2015, we captured and marked ducks with GPS transmitters in the Suisun Marsh using hand-held dip nets, rocket nets, and baited funnel traps (Haramis and others, 1982; Drewien and Clegg, 1992; Schemnitz and others, 2009; McDuie and others, 2019a, b). Many of these marked individuals wintered in the Central Valley before migration to breeding areas, enabling us to study their movements and ecology in the Central Valley during fall–winter (October 1–March 31). We captured ducks during three periods: fall, before the hunting season (September–October); winter, shortly after the hunting season (late January to March); and nesting females in spring/summer (April–July), in an extended effort as part of the overall research program to acquire data throughout their annual life cycle. We captured ducks nesting on Grizzly Island Wildlife Area (38.13831°N, 121.9781°W), hunting clubs in Suisun Marsh, and at Howard Slough State Wildlife Area in the Sacramento Valley (39.46726°N, 121.8774° W). Blue-winged and cinnamon teal ducks were captured at various locations within California, Oregon, Idaho, Colorado, Nevada, Washington, and Utah.

Ducks were fitted with Ecotone® GPS-GSM SAKER L series solar rechargeable electronic transmitters that communicate using the cellular network. We attached transmitters to adults with back-mounted body harnesses. Global Positioning System transmitters deployed on smaller teals weighed 14 grams (g) and transmitters for the remaining species weighed 17g, which is within acceptable body weight limits for birds (3–5 percent; Cochran, 1980; Gaunt and others, 1997; Kenward and others, 2001; Phillips and others, 2003). Telemetry GPS relocation points (hereafter "locations") with date and time were transmitted to Ecotone (http://telemetry.ecotone.pl) through text message. These transmitters allowed accurate (less than or equal to 10 m; most about 5 m) and frequent (30 minutes to 6-hour intervals depending on transmitter battery charge) data. When the battery reached a minimum critical power level, the logger switched to a 6-hour interval until it was sufficiently recharged to revert to obtaining locations at shorter intervals.

Translation of Dynamic Open-Water Data to Waterfowl Habitat Maps

We processed open-water data to produce three series of maps that differed in the translation of dynamic waterfowl habitat in California. Each map series was based on, or derived from, Point Blue's open-water datasets comprising 98 raster mosaics (hence a series). The first in the series was the dynamic open-water data itself, representing a direct translation from open-water habitat to waterfowl habitat; that is, only open-water pixels (in other words, classified as "water" in dynamic water data) constituted waterfowl habitat. The second series of waterfowl habitat maps included a buffer around water pixels to represent adjacent areas used for roosting and the occurrence of densely vegetated emergent marsh areas frequently used by some waterfowl species. The final waterfowl habitat map initially incorporated a single pixel-width thinning process using the Shrink tool in ArcGIS v10.4.1 (Environmental Systems Research Institute, 2018) to remove isolated pixels/regions where water was estimated to occur and then extrapolating out from larger water sources to include adjacent areas for roosting and dense vegetation. This processing step resulted in a minimum open-water area of about one hectare (ha) being necessary for waterfowl habitat to be predicted.

Preparation of Duck Location Data

We prepared telemetry data for analysis with the habitat data by filtering the telemetry data to represent local use by ducks of land cover/management types for the wintering period (October 1–March 31). We defined biological activity for each duck location as roosting or feeding (local use of land cover/management types) versus "other" (local flight, migration, nesting, raising brood, and molting; appendix 2; C. Overton, oral commun., September 1, 2018). We constrained our analysis to roosting and feeding locations of ducks during October–March 31. The complete telemetry dataset (before filtering the data) for years 2015–18 contained greater than 507,000 GPS point locations. Of those locations, 208,267 were in California, of which 71,198 locations were during October 1–March 31 (the period analyzed) and classified as roosting or feeding activity; however, another 9 percent of these were excluded from our analysis because they were outside the geographic extent of the open-water data. The final telemetry dataset we used in analyses with water data included 66,588 duck locations from 221 ducks between October 1 and March 31 of years 2015–18.

Integration of Habitat Maps and Duck Locations

To manage duck telemetry and dynamic open-water data, we developed a data table with common fields linking dates of telemetry locations with open-water data that we used to intersect locations with these images. By relating water and duck location data that were most similar temporally, we could evaluate the most representative water data to actual conditions on the ground with respect to space-use patterns by ducks. Next, we developed R scripts (R v3.3.2; R Core Team, 2018) for iteratively intersecting telemetry locations with each of 98 raster mosaics for dynamic open-water data provided by Point Blue and each of the other two series of habitat maps derived from the open-water data. Using the R scripts and the Raster package (Hijmans, 2017), we classified each duck location as occurring in habitat, or not. Our scripts allowed us to extract from each series of habitat maps, the nearest map to the date that each telemetry location was recorded, and then attribute "habitat" or "non-habitat" to each location using the temporally matching map. The R scripts allowed us to conduct iterative looping to assign appropriate rasters to telemetry points by nearest date within 8 days between recording Landsat imagery and telemetry points. In R looping, the raster with the appropriate date could be selected for intersection with a given duck location. Consequently, an estimated 19,576,872 (66,588 duck locations x 98 raster mosaics per series x 3 series of maps) data combinations were used to extract binary (0=non-habitat, 1=habitat) values from maps and attribute duck locations for subsequent analysis. Using duck locations attributed with habitat map values, we calculated the proportion of waterfowl locations occurring within identified habitats.

Evaluation of Waterfowl Habitat Maps

Each of the habitat maps was evaluated based on two factors: (1) the proportion of California within the extent of open-water data described as habitat and (2) the proportion of waterfowl locations occurring within identified habitats. The former metric was calculated as a proportion of binary classified habitat presented in attribute tables for each map using ArcGIS v10.4.1. The second metric was calculated by intersecting each telemetry location with the temporally consistent habitat raster. This intersection resulted in two potential classifications for each location, in non-habitat or in habitat, which subsequently were totaled and summarized as the proportion of locations intersecting classified habitat.

Distance of Feeding Locations from Roosting Locations

We examined the effect of drought on distributions of ducks by evaluating differences in spatial distributions of duck locations within and among years: 2015–16 (drought), and 2016–17 and 2017–18 (non-drought). Even within years, seasonal limitation in flooded habitats could result in drought-like conditions that could affect use of space by ducks. The distribution of nighttime foraging locations relative to primary roost locations was assessed for seasonal and inter-annual variation corresponding with two hypotheses regarding droughts: (1) droughts reduce habitat availability and or quality resulting in, on average, farther distances traveled to obtain food throughout the winter or (2) reduced habitat availability or quality results in more rapid degradation in the habitats closer to roost sites resulting in increased foraging distances through the winter (could occur in drought or non-drought years, although possibly more apparent in drought years). To quantify foraging distances, we calculated distances between duck nighttime (feeding) locations and primary sanctuaries used for daytime roosting. For this analysis, we first divided winter relocation data into two time periods: daytime–representing primarily roosting behavior, and nighttime—representing most feeding activity (Miller, 1985). Using ArcGIS v10.4.1, we calculated relocation point density for daytime locations using data for all locations within California. Estimated point density was calculated per 9-hectare pixel (300 m per side) and used to identify local peaks of daytime use characterizing the greatest densities of roosting ducks (in other words, primary roost locations). We identified 16 such locations in the Central Valley and Suisun Marsh that primarily represented sanctuary areas on several State Wildlife Areas (CDFW) and National Wildlife Refuges (USFWS) that were closed to hunting, but also included Cosumnes River Preserve and privately owned wetlands (fig. E2).

Next, we calculated the Euclidean distance to the nearest of these daytime roost locations from each nighttime (foraging) location. The distribution of relocation data was used as a measure of duck distribution (or space use) relative to these primary roosts. Increased distance from these roosts could mean increased dispersal between roosting and foraging locations, selection of alternative lesser used roost locations (although some individuals could use these consistently), or a combination of each. In each case, the difference in distribution of nighttime locations or use of alternative roost locations reflects a potential cost to duck fitness resulting from this behavior. The two primary costs are differential energetic demand due to differences in forage flight distance (increased demand with greater distance traveled) or differential survival risk due to use of alternative roost locations, which can be less safe or familiar to ducks. Flight-induced increase in energetic demand could result in energy deficit to impact survival or subsequent reproductive output during the breeding season.

Figure E2. Primary daytime roosting areas (green dots; n=16) for ducks wintering in the Central Valley and Suisun Marsh determined from densities of telemetry points aggregated across the study duration (months October–December and the following January–March of years 2015–18).

Analysis was separated between two spatial regions: (1) Suisun Marsh, which contains primarily seasonally flooded wetlands managed specifically for waterfowl food production and has little limitation in available water and flooded habitat due to proximity to tidal inflow and inflow from Sacramento and San Joaquin Rivers and (2) other areas in California which include a mix of seasonal marshland and flooded agricultural habitats within the Central Valley. Suisun Marsh is relatively isolated from adjacent waterfowl habitat (for example, in the Central Valley) and also was the primary region where waterfowl were captured and released; both factors result in a much greater point density within that region necessitating separate consideration of drought impacts for the two regions. The comparative spatial and temporal hydrologic “stability” of flooded Suisun Marsh habitats compared to those in the Central Valley (Reiter and others, 2015) provided an opportunity to compare duck distributions between the two regions to explore possible effects of hydrologic spatiotemporal variability on duck behavior, which in turn could influence fitness.

Interannual Overlap in Space Use

We compared overlap of duck locations between consecutive years (2015–16, 2016–17, and 2017–18) to assess interannual habitat stability in relationship with drought, habitat management (daytime roosts and night feeding sites), and in two regions (Suisun Marsh and California except Suisun Marsh). Previous research showed that movement distances within this dataset generally were greater than 300 m when birds switched areas of use (McDuie and others, 2019b). This research suggests that two duck locations within 300 m of each other represent the use of the same resource(s). Thus, we evaluated the proportion of duck locations in a given year that were less than 300 m from locations in each of the other years from October 1 to March 31 to represent use of the same resources between years. Coincident use of space across years suggests that the landscape is relatively stable, in terms of where and when flooding occurs, or that birds are actively selecting those portions of the landscape that are consistently flooded even in drought years.

Using ArcGIS v10.4.1, for each of the three sets of years, we created 300-m buffers for all duck locations in California, most of which were in Suisun Marsh or the Central Valley. We calculated the proportion of duck locations in a given year that intersected buffered areas from another year, which we did for all year combinations. This metric indicated the extent that ducks consistently used the same space (flooded areas) across years. We conducted this analysis for each period during the day (day versus night), region (Central Valley versus Suisun Marsh), and among years: 2015–16 (drought), and 2016–17 and 2017–18 (non-drought).

We hypothesized that areas used by ducks during drought (2015–16) would correspond less with areas used during non-drought (2016–17, 2017–18) than areas used in sets of non-drought years correspond with each other, related to a more restricted distribution of habitats during drought for ducks to select. We additionally thought that areas used in daytime relative to night would be more consistent across years because of reliable water management for sanctuaries on wildlife areas and national refuges used as daytime roosts. We also hypothesized that areas used in Suisun Marsh would be more consistent across years because water availability is less limited by drought in Suisun and most habitats are flooded each year (Reiter and others, 2015).

Results and Discussion

Our analysis indicated a strong direct relationship between duck locations and classified habitat derived from open-water data during the wintering period (October–March), which validated the application of the dynamic water data to create new maps for identifying flooded areas used by ducks. Species associated with large open bodies of water including gadwall and northern shoveler were readily identified in open water. By contrast, species that use emergent marsh or linear habitats to a great extent, including mallard and cinnamon teal, were determined to occur directly within water only about 60 and 72 percent of the time, respectively. However, after eliminating isolated water pixels/regions and extrapolating larger areas of water, we could relatively identify flooded landscape areas available as habitat for ducks.

Our findings indicated that nighttime feeding locations of ducks were concentrated nearby primary roosts and that foraging distances depended on hydrologic dynamics of location (Suisun Marsh versus California excluding Suisun Marsh) and time of season. Our results from evaluating overlap of locations between consecutive years indicated that habitats in areas with extremely reliable water supplies (for example, Suisun Marsh) could receive consistent use by ducks year after year.

Evaluation of Waterfowl Habitat Maps

Performance of dynamic water data for identifying key flooded areas will likely depend on duck species or the biological activity being assessed. Because species vary to some extent in the types of flooded habitats they prefer, error in classification of some flooded features (habitat) as “dry” (non-habitat) could explain differences among species in odds of being classified as water (percentage as habitat/percentage as non-habitat, table E1). For example, odds of classifying mallard locations as occurring in habitat was much lower than for other species. Conversely, blue-winged teal, gadwall, northern pintail, and northern shoveler had relatively higher odds of being in water than for other species. At 30-m resolution, the Landsat data used to derive dynamic water data was too coarse to identify linear or small water features on the landscape used by ducks. Some duck species appear to prefer relatively large areas of open water (for example, northern pintail, northern shoveler, gadwall), whereas others were frequently detected using apparent water delivery or drainage canals (for example, mallard and cinnamon teal; C. Overton, oral commun., September 1, 2018).

The accuracy of each waterfowl habitat map we developed was demonstrated by the amount of habitat the resulting map indicated existed within the Central Valley and the propensity for duck locations to occur within delineated habitat (table E2).

Table E1. Proportion of telemetry locations for each of the seven dabbling duck species (from October 1 to March 31, during the study period January 2015–September 2018) that were classified as occurring in habitat (or not) in the Central Valley and Suisun Marsh (California) by using the final translation habitat map derived from the dynamic open-water dataset.

[%, percent]

Species	Non-habitat (%)	Habitat (%)	Odds of being in water[1]
American wigeon	13	87	6.7
Blue-winged teal	1	99	67.7
Cinnamon teal	15	85	5.8
Gadwall	4	96	22.1
Mallard	25	75	3.0
Northern pintail	9	91	9.7
Northern shoveler	7	93	14.0
Average	11	89	8.4

[1]Odds equals percent as water/percent as dry.

Table E2. Comparison among waterfowl habitat mapping products in the estimated proportion of habitat on the California landscape in October–March of 2015–18 and the proportion of duck locations occurring in habitat derived from open-water data.

[%, percent]

Map translation[1]	Mean habitat percent in classified image (%)	Range in area representing habitat (%)	Mean percent of duck locations occurring within habitat (%)
Direct	7.8	1.2–38.8	76
Adjacent area	29.2	5.2–85.6	96
Adjacency after shrinkage	10.3	2.0–46.1	87

[1]Direct equals Point Blue dynamic open-water images; adjacent area equals interim dataset that accounted for waterfowl habitat adjacent to open-water areas; adjacency after shrinkage equals final dataset with pixel thinning to eliminate over-inflation of habitat area created in adjacent area dataset.

Our initial map, which was a direct translation from open-water occurrence to waterfowl habitat, indicated that classifiable portions of the Central Valley contained 1–39 percent waterfowl habitat (table E2). These values varied owing to the location and amount of identified cloud cover (0–99 percent) present in the mosaicked Landsat images. Variation among maps tended to be lower early in the fall (early October) or late in the winter (March), which also corresponded to periods with less cloud cover. Because water, and therefore waterfowl habitat, is somewhat spatially clustered within the Central Valley, comparing partially complete maps of the valley could result in markedly different amounts of habitat if there is little overlap among the spatial extents of the two maps. When assessing the proportion of duck locations within the identified habitat for this initial "direct translation" map, nearly 25 percent of ducks were outside the identified habitat locations during the winter. Subsequent analysis of location distribution indicated that most of the locations identified in non-habitat were within 100 meters of habitat. In addition, there were substantial differences in the propensity for a location to occur within identified habitat among species (table E1). These two factors suggested that the direct translation map fails to identify habitat occurring in "mixed pixels" such as pond margins and levees where waterfowl will frequently roost and for densely vegetated marshes used by species such as mallard and cinnamon teal.

To overcome these issues, we translated a second habitat map that accounted for adjacency of waterfowl habitat to open-water areas. This map was designed to include those features used frequently by all waterfowl or those of particular species that result in lower pixel-level classification as open water. The proportion of the Central Valley that provides waterfowl habitat, as indicated by this translation, averaged 29 percent and ranged from 5 percent to almost 86 percent among individual classifiable Landsat scenes (table E2). The proportion of duck locations within habitat was 96 percent. The amount of available waterfowl habitat in the Central Valley peaks in the winter and was sometimes very high at smaller spatial scales; however, the amount of habitat indicated by this map was inflated by widely dispersed and isolated open-water habitats identified in maps. Most of the isolated open-water pixels represented relatively infrequent errors of commission in the open-water classification where dry pixels are erroneously determined to be wet. The rates of these errors were high for some images, and in most cases, the incorrectly classified pixels did not represent suitable waterfowl habitat.

Our final map translation incorporated a pixel thinning process to remove isolated and small bodies of water that were determined to provide limited or no waterfowl habitat. According to this translation, the Central Valley provided an average of 10-percent waterfowl habitat (range=2–46 percent; table E2). Approximately 87 percent of duck locations were within these identified habitats. The remaining 13 percent of locations predominantly represented birds flying over land, errors in the open-water classification resulting from unidentified cloud cover, and limitations in our translation that resulted in very heavily vegetated marshes (often used by a subset of species monitored) that failed to be classified as habitat. Despite these sources of error, we provided a useful translation of the dynamic open-water classification to a waterfowl habitat map.

Distance of Feeding Locations from Roosting Locations

Nighttime feeding locations of ducks were most concentrated near primary daytime roosting sites. In California, excluding Suisun Marsh, about 50 percent of nighttime feeding locations were within 10 kilometers (km) of primary roosts. In Suisun Marsh, greater than 90 percent of nighttime feeding locations were within 10 km of primary roosts. Nighttime duck locations in California, except for Suisun Marsh, were relatively farther from primary roost sites in a drought period (years 2015–16) during months when managed flooding of habitat had peaked historically (December–January, fig. E3; Central Valley Joint Venture, 2006). Additionally, ducks were distributed closer to roosts during the early season (October–November) of a non-drought year (2017–18, fig. E3). This placement provides tentative support for both hypotheses: that ducks fly farther from roost locations throughout the wintering period during drought versus non-drought, and they fly farther as the season progresses. During drought, food that is nearby roost locations could be initially inadequate, and food also could become limited as the season progresses. Alternatively, instead of the primary roost sites that we identified, ducks could use secondary roost sites during drought that are closer to foraging areas. Other month-year combinations were similar to each other in their distances between daytime roosts and nighttime feeding locations. Thus, drought-related and seasonal effects on habitats and food supplies can be cumulative and much greater together than each effect alone on food supplies. Future analysis could examine whether during drought, habitat availability relative to distance from roost sites, matches relative distributions of duck locations. In all month-years, nighttime feeding locations in Suisun Marsh were consistently near primary roosts based on a large sample of ducks relative to the area of available habitat, isolation of habitats from other regions in California, and water for management of wetlands was readily available (fig. E4). The greatest (although only moderately different) distances between roosts and nighttime locations in Suisun Marsh occurred during February–March of 2015–16 and could have been related to drought or late-season effects on habitat abundance or quality. Results indicate that when and where water to support habitats is limited, ducks may respond by flying farther to feed, and habitat managers may be able to mitigate impacts on duck survival or body condition by reallocating water to foraging habitats near roosts.

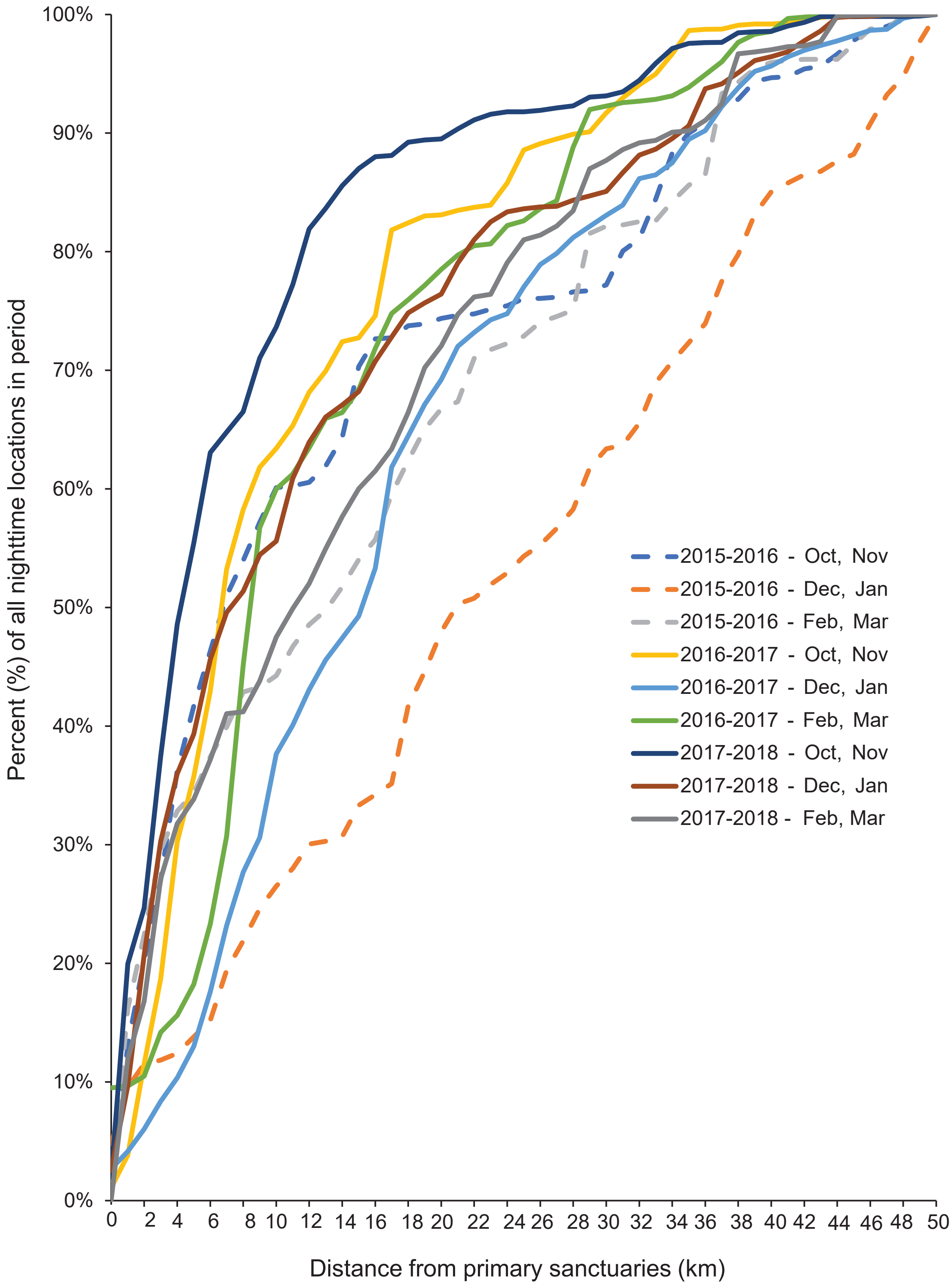

Figure E3. Distances (in kilometers; km) between nighttime locations and primary daytime roosting sites of ducks in California, excluding the Suisun Marsh (predominantly the Central Valley), during October–December and the following January–March (wintering period) in years 2015–18. Spatial distribution is represented as distance (in kilometers; km) of nighttime locations from the nearest primary sanctuary used by ducks during the daytime. Dashed lines represent drought years (2015–16) and solid lines represent non-drought years (2016–17, 2017–18).

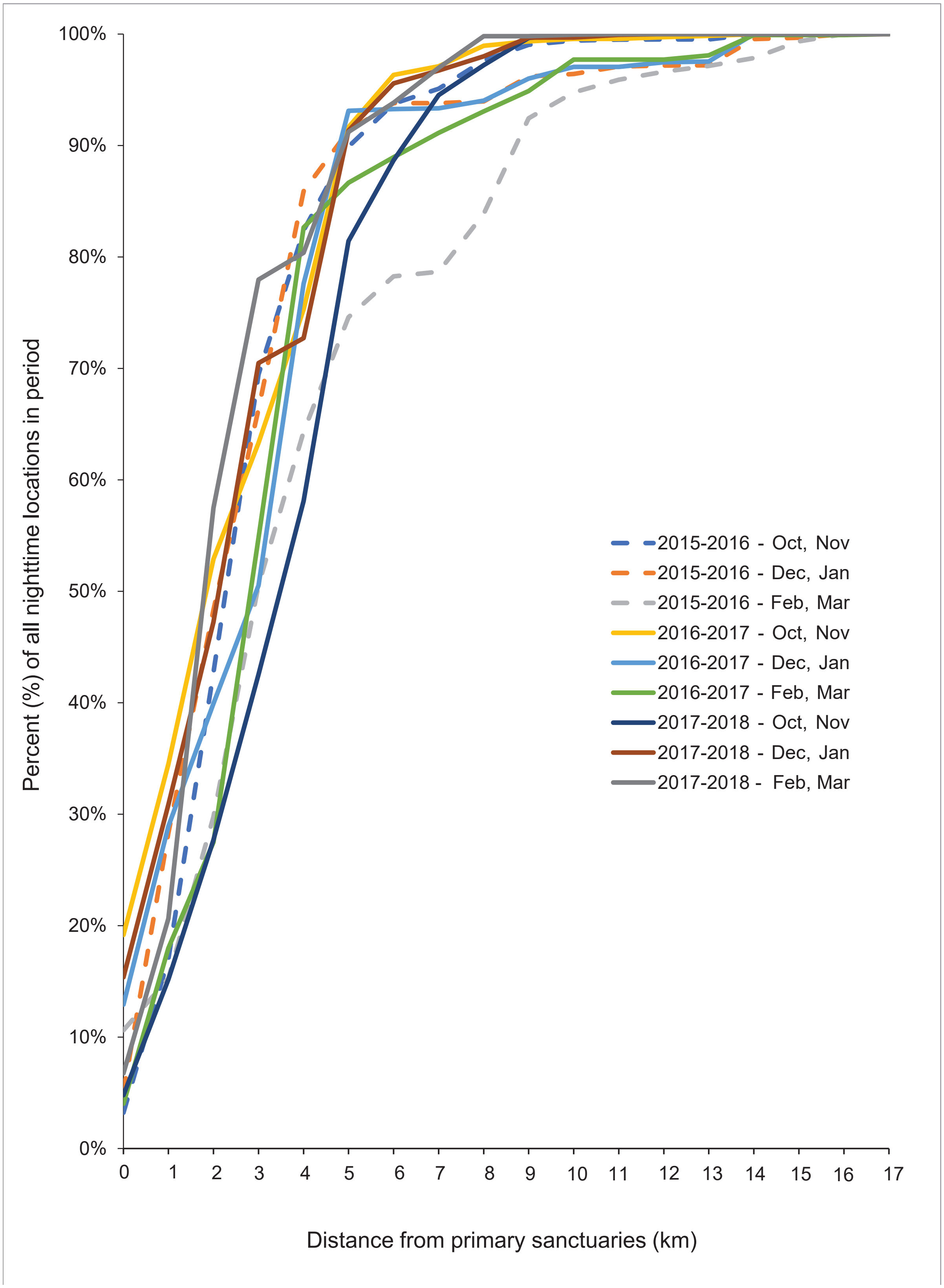

Figure E4. Spatial distribution of nighttime locations of ducks in the Suisun Marsh of California during October–December and the following January–March (wintering period) in years 2015–18. Spatial distribution is represented as distance (kilometers; km) of nighttime locations from nearest primary sanctuary used by ducks during the daytime. Dashed lines represent drought years (2015–16) and solid lines represent non-drought years (2016–17, 2017–18).

Interannual Overlap in Space Use

In evaluating the overlap of duck locations (within 300 m) of a given year with locations of the other two sets of years, our results indicated substantial differences in interannual space use between Suisun Marsh and the region of California that excluded Suisun Marsh. We observed less difference in the extent of interannual overlap between daytime and nighttime locations or sets of drought and non-drought years for both regions. Space use by ducks among years 2015–16, 2016–17, and 2018–19 (in other words, where and when ducks used individual flooded habitats) was relatively inconsistent in California, excluding Suisun Marsh (table E3). Approximately 20–40 percent of duck locations in any given year overlapped the same areas used in other years. In other words, most (60–80 percent of locations) were more widely distributed than 300 m. This relative lack of location correspondence might suggest that areas where habitats were flooded were relatively unpredictable between years, but also might reflect an abundance of accessible flooded habitats that were distant from each other. By contrast, space use in Suisun Marsh was more similar among years (approximately 70–85 percent of overlap in locations; table E4). In California, excluding Suisun Marsh, space use by ducks during the daytime was more similar than nighttime locations among years with a percentage overlap of 28–42 percent versus 21–28 percent, respectively (table E3). Greater similarity in daytime compared to nighttime use tentatively supports the hypothesis that roosts, which are typically used in the daytime, are more hydrologically stable and accessible to ducks. We could not discern clear interannual patterns of daytime compared to nighttime use in Suisun Marsh or among drought and non-drought years for either region (tables E3 and E4).

Implications for Research and Habitat Management

Results from our duck telemetry data indicated that Point Blue’s Water Tracker has significant potential to represent dynamic habitats used by ducks in California to help predict space use and distributional patterns of ducks. However, from other results of this research, we also determined that flooded habitat areas were not used equally by species. Using telemetry data, we identified spatial and temporal patterns in use of foraging habitats related to distances from primary roosting areas; flooded habitats that are closer to roosts will be used more for feeding than those that are farther. Though during drought, ducks may be forced to fly farther in search of food in the region of California that excluded Suisun Marsh. From this finding, we infer that reallocation of water supplies for feeding habitats nearest to roosts could help to limit impacts on ducks (for example, potentially substantial energetic or survival costs). However, we also think additional research is necessary to learn what other factors may influence use of space and habitats by ducks. The relative stability of flooded habitats through time is another factor that may be important in determining space use and distributions of ducks on the landscape, which in turn may have demographic consequences on ducks. Daytime roosts, which are thought to have more consistent water supplies, appear to have been used somewhat more frequently across years than areas generally used at night. One possible reason Suisun Marsh had a higher intensity of use than the region excluding Suisun Marsh may have been related to the consistently abundant water in Suisun Marsh to support habitats each year.

Table E3. Percentage of overlapping duck locations (within 300 meters) in California, excluding Suisun Marsh, during October–March of 2015–16 (drought), 2016–17 (non-drought), and 2017–18 (non-drought), which represents overlapping space use by ducks in alternate years.

[Units in percent; Year headings represent alternate years being compared with year of use.]

Year of use	2015–16	2016–17	2017–18
	Daytime		
2015–16	100	36	28
2016–17	41	100	40
2017–18	33	42	100
	Nighttime		
2015–16	100	25	25
2016–17	24	100	21
2017–18	28	24	100

Table E4. Percentage of overlapping duck locations (within 300 meters) in the Suisun Marsh, California, during October–March of 2015–16 (drought), 2016–17 (non-drought), and 2017–18 (non-drought), which represents overlapping space use by ducks in alternate years.

[Units in percent; Year headings represent alternate years being compared with year of use.]

Year of use	2015–16	2016–17	2017–18
	Daytime		
2015–16	100	76	80
2016–17	85	100	84
2017–18	78	63	100
	Nighttime		
2015–16	100	70	75
2016–17	84	100	70
2017–18	81	70	100

In future research, telemetry data could be applied to understand additional utility or limitations for using dynamic water data to characterize waterfowl habitats. Clouds in Landsat scenes reduced the number of duck locations with water data that we could effectively use for analysis of relationships between dynamic water and duck locations. Open-water data could be augmented with a secondary data product already developed by Point Blue that corrects for cloud-masking effects by filling masked areas using predictions of water extent based on historical data. Using the cloud-filled open-water data might allow calculation of distance, neighborhood statistics, and classification (water, dry) for all telemetry locations.

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Appendix 1. Reiter and others, 2018. Publication as a Product of Objective 1

In the published research titled “Impact of extreme drought and incentive programs on flooded agriculture and wetlands in California’s Central Valley,” (Reiter and others, 2018) researchers studied the effects of extreme drought on the timing and extent of flooded habitats in the Central Valley used by waterbirds during July–April (non-breeding season). The research also investigated the efficacy of habitat incentive programs, including The Nature Conservancy’s Bird Returns and The Natural Resources Conservation Service’s Waterbird Habitat Enhancement Program (WHEP), at mitigating drought-related loss of habitat.

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Reiter, M.E., Elliott, N.K., Jongsomjit, D., Golet, G.H., and Reynolds, M.D., 2018, Impact of extreme drought and incentive programs on flooded agriculture and wetlands in California’s Central Valley: PeerJ, v. 6, no. e5147, 22 p., https://doi.org/10.7717/peerj.5147.

Impact of extreme drought and incentive programs on flooded agriculture and wetlands in California's Central Valley

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ABSTRACT

Background: Between 2013 and 2015, a large part of the western United States, including the Central Valley of California, sustained an extreme drought. The Central Valley is recognized as a region of hemispheric importance for waterbirds, which use flooded agriculture and wetlands as habitat. Thus, the impact of drought on the distribution of surface water needed to be assessed to understand the effects on waterbird habitat availability.
Methods: We used remote sensing data to quantify the impact of the recent extreme drought on the timing and extent of waterbird habitat during the non-breeding season (July–May) by examining open water in agriculture (rice, corn, and other crops) and managed wetlands across the Central Valley. We assessed the influence of habitat incentive programs, particularly The Nature Conservancy's BirdReturns and The Natural Resources Conservation Service's Waterbird Habitat Enhancement Program (WHEP), at offsetting habitat loss related to drought.
Results: Overall, we found statistically significant declines in open water in post-harvest agriculture (45–80% declines) and in managed wetlands (39–60% declines) during the 2013–2015 drought compared to non-drought years during the period of 2000–2011. Crops associated with the San Joaquin Basin, specifically corn, as well as wetlands in that part of the Central Valley exhibited larger reductions in open water than rice and wetlands in the Sacramento Valley. Semi-permanent wetlands on protected lands had significantly lower (39–49%) open water in the drought years than those on non-protected lands while seasonal wetlands on protected lands had higher amounts of open water. A large fraction of the daily open water in rice during certain times of the year, particularly in the fall for BirdReturns (61%) and the winter for WHEP (100%), may have been provided through incentive programs which underscores the contribution of these programs. However, further assessment is needed to know how much the incentive programs directly offset the impact of drought in post-harvest rice by influencing water management or simply supplemented funding for activities that might have been done regardless.
Discussion: Our landscape analysis documents the significant impacts of the recent extreme drought on freshwater wetland habitats in the Central Valley, the benefits of incentive programs, and the value of using satellite data to track surface water and

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Figure 1.01. Published research (title, year: "Impact of extreme drought and incentive programs on flooded agriculture and wetlands in California's Central Valley," 2018) supported by this project.

waterbird habitats. More research is needed to understand subsequent impacts on the freshwater dependent species that rely on these systems and how incentive programs can most strategically support vulnerable species during future extreme drought.

Subjects Conservation Biology, Ecology, Freshwater Biology
Keywords Agriculture, California, Drought, Water, Wetlands, Waterbirds, Habitat incentive program, Central Valley

INTRODUCTION

The Central Valley of California is a region of hemispheric importance for waterbirds (*Gilmer et al., 1996*; *Shuford, Page & Kjelmyr, 1998*; *Central Valley Joint Venture (CVJV), 2006*). With 90% of the historically occurring natural wetlands in the Central Valley gone (*Frayer, Peters & Pywell, 1989*), agricultural crops that are flooded post-harvest and hydrologically-managed wetlands are essential resources for migratory waterbirds (*Elphick & Oring, 1998*; *Dybala et al., 2017*; *Shuford & Dybala, 2017*). However, provisioning these crops and wetlands as waterbird habitat is dependent on a highly managed water system governed by dams, canals, water control structures, and water rights (*Hanak & Lund, 2012*). Meanwhile, the availability of water is dynamic both within and among years (*Reiter et al., 2015*; *Reynolds et al., 2017*). Future projections suggest that the inter-annual variability in the amount of waterbird habitat may increase with time due to the complex interactions of climate and human water management, even if long-term declines in average precipitation are not projected to be substantial (*Matchett & Fleskes, 2017*), making it critically important to understand how to manage wetlands and incentive-based habitat programs through extremes.

Between 2013 and 2015, the Central Valley of California and a large part of the western United States sustained an extreme drought (*Griffin & Anchukaitis, 2014*; *Robeson, 2015*). Because California's water is so highly managed, anthropogenic factors play a large role in determining when and where drought impacts appear on the landscape (*Hanak & Lund, 2012*). Further, drought status, as measured by changes in precipitation, within the Central Valley may be less important to the availability of water in the Valley than the amount of snow pack in the surrounding mountain ranges which are the source of the Valley's water (*Carle, 2009*). Previous analyses highlighted that while drought conditions across California's Central Valley may be observed as a reduction in surface water in the southern Central Valley in the year of the drought, often multiple years of drought are required to see changes in the northern portion of the Central Valley (*Reiter et al., 2015*). The recent extreme and multi-year drought affecting California provides opportunity to gain additional insights into how more prolonged and extreme variations in the hydrology of the Sacramento and San Joaquin River watersheds may influence the distribution of waterbird habitat. This is especially important given that the incidence of such extremes is projected to increase in the future (*Snyder, Sloan & Bell, 2004*; *Matchett & Fleskes, 2017*).

Figure 1.01. —Continued

In response to the drought, water restrictions (e.g., Term 91: Stored Water Bypass Requirements) were put into place in the Central Valley in the fall of 2014. The effects on the distribution of surface water caused by water restrictions, increasing water costs (*Howitt et al., 2014*), and lack of precipitation, needs to be assessed to understand impacts on waterbird habitat availability. Concurrent with this recent drought was the implementation of two incentive programs to help offset the cost of flooding agricultural fields to provide wetland habitat for migratory waterbirds (i.e., The Nature Conservancy's BirdReturns program (*Reynolds et al., 2017*; *Golet et al., 2018*); Natural Resources Conservation Service's Waterbird Habitat Enhancement Program (WHEP; *Strum, Sesser & Iglecia, 2014*)). The extent to which these incentive programs offset habitat losses due to the drought is not known. BirdReturns focused specifically on shorebirds, providing habitat <10 cm deep, in September and October and then again February to early April. WHEP incentivized flooding from November to February, though unlike BirdReturns, did not have a target water depth, but then staggered the timing of draining of those fields starting 1 February and lasting to 21 February to provide habitat into March.

Previous analysis of Central Valley water availability during drought quantified the extent of open surface water in the Central Valley between July and December for 2000–2011 (*Reiter et al., 2015*). To better characterize the magnitude and impacts of the recent extreme drought and to assess the relative contribution of flooded habitat as the result of incentive programs, analyses of more recent data compared to longer-term estimates (2000–2011; *Reiter et al., 2015*) of water extent were needed. Hence, our objectives with this study were to:

1. Quantify the impact of the extreme drought between 2013 and 2015 on the timing and extent of available waterbird habitat (flooded agricultural fields and managed wetlands) during the non-breeding season (July–May) across the Central Valley.
2. Assess the influence of two incentive programs, BirdReturns and WHEP, at offsetting waterbird habitat loss resulting from drought.

METHODS AND MATERIALS

Study area

We considered the entire Central Valley Joint Venture (CVJV) primary planning region (*Dybala et al., 2017*) to be the focal area for this study. The CVJV is a coalition consisting of 21 State and Federal agencies, private conservation organizations and one corporation that collaborates to achieve the common goal of providing for the habitat needs of migrating and resident birds in the Central Valley of California; a region of international importance for migratory waterfowl (Anseriformes) and shorebirds (Charadriiformes; *Central Valley Joint Venture (CVJV), 2006*). We further divided up the region into five basins according to *Shuford & Dybala (2017)* and used only the Sacramento Valley Basin and the San Joaquin Basin for some analyses (Fig. 1). The Central Valley falls completely within the Great Valley ecoregion (*Hickman, 1993*), and extends >400 km north to south and up to 100 km east to west; bounded by the Sierra Nevada, Cascade, and California

Figure 1.01. —Continued

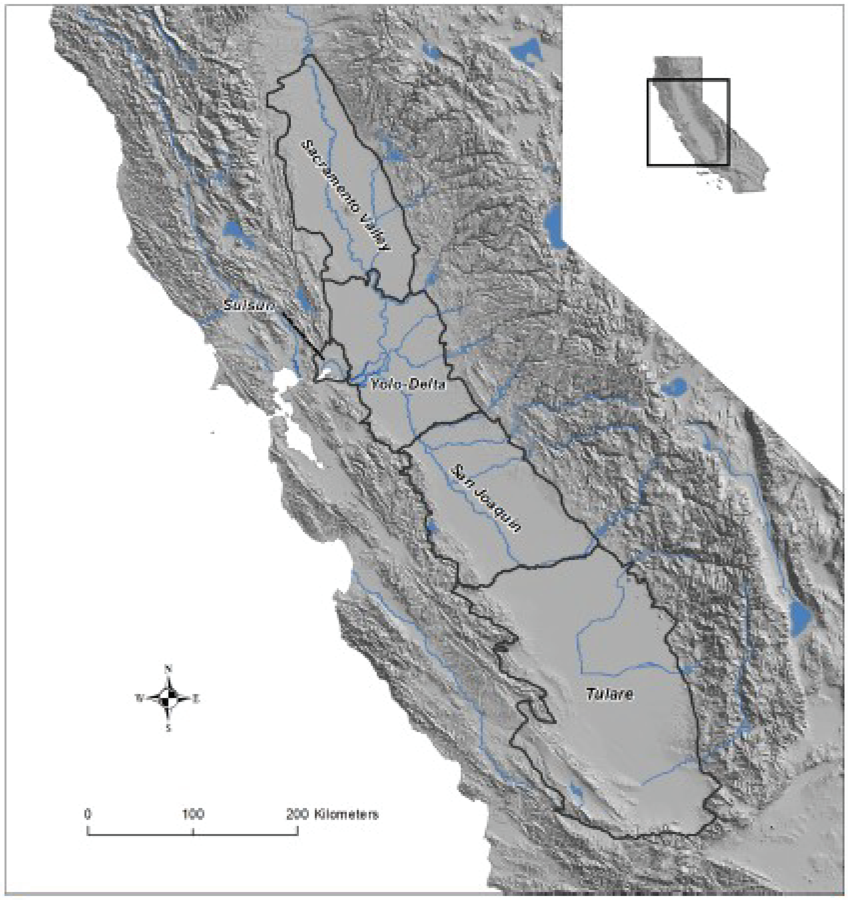

Figure 1 Map of the Central Valley study area in California, USA. The Central Valley Joint Venture boundaries and five basins of the Central Valley: Sacramento Valley Basin, Sacramento-San Joaquin River Delta [Yolo-Delta], San Joaquin Basin, Suisun Basin, and Tulare Basin. Data source: USGS and Central Valley Joint Venture (U.S. Fish and Wildlife Service).

Full-size DOI: 10.7717/peerj.5147/fig-1

Coastal Range mountains. The Central Valley climate is generally cooler and wetter in the north (Sacramento Valley Basin) than in the south (San Joaquin Basin and Tulare Basin). Water allocation and use in the Central Valley is highly managed and the southern portion of the Valley often relies on water being transferred for use from the north through contractual agreements ("water transfers"; *Hanak & Lund, 2012*). Consequently, there is generally less flooded agriculture in the southern Central Valley and higher year to year variability in flooding compared to in the north (*Reiter et al., 2015*). The majority of surface water in the Central Valley originates from snow pack in the adjoining Sierra Nevada and Cascade mountains (*Carle, 2009*).

Figure 1.01. —Continued

Data and models

We derived data on the distribution of open water (<30% vegetated) across the Central Valley for 1 July–15 May of the following year, using satellite imagery and the supervised classification remote sensing techniques of *Reiter et al. (2015)*. We used Landsat 5 Thematic Mapper for the period of 2000–2011 and Landsat 8 Operational Land Imager and Thermal Infrared Sensor for the period of 2013–2015. Because these sensors have different numbers of bands and slightly different wavelengths within each band, we developed separate boosted regression tree models for each satellite (*Elith & Leathwick, 2009*). We used data combined from ground and aerial surveys (n = 10,221 for our Landsat 5 model and n = 27,058 for our Landsat 8 model) to develop our models and to compare the relative bias associated with the predictions from each model. To prevent classification bias influencing our inference in this analysis, we bias-corrected the estimates of open water by the average difference between the true and estimated open water calculated using the ground-truth data for each sensor. We used separate correction factors for wetlands, rice, corn, and other crops.

We evaluated the timing and extent of open water from July to May for the Central Valley across several waterbird habitat cover types (seasonal and semi-permanent wetlands, rice [*Oryza* spp.], corn [*Zea mays*], and other suitable field crops and row crops [e.g. *Triticum* spp.; *Gossypium* spp.; *Solanum lycopersicum*]; see *Dybala et al., 2017*). To derive the amount of water by specific cover types (and to ensure that changes in water were not the result of changes in base acreages of potential habitat), we used two layers for wetlands and for agriculture representing the early 2000s (*Stralberg et al., 2011*; *Homer et al., 2007*) and then more recent habitat maps (2007–2014; *Petrik, Fehringer & Weverko, 2014*; Data S10). We considered cover types that were the same in both time periods as the baseline for assessing the proportion of each cover type that was open water. We overlaid each of the open water layers (2000–2015) on the habitat base layer to derive the proportion of each cover type that was open water.

Because the dynamics of water in the Central Valley are often non-linear, we followed *Dybala et al. (2017)* and used generalized additive mixed models (GAMMs; *Wood, 2006*; *Wood & Scheipl, 2014*) to assess the influence of time of year, drought, precipitation, region, and protected status (for wetlands only as most agriculture land is privately owned and not protected) on the proportion of open water in selected cover types between 1 July and 15 May of the following year. We evaluated GAMMs separately for each cover type. We fit a set of five models to agricultural crop data for 2000–2015 and six models to wetland cover type data (see covariate descriptions below). We filtered our data to only include satellite images with <50% cloud cover and then weighted observations in the model by the percent that was cloud free (50–100%). We included a random effect of water year to account for correlation among observations within the same year and an individual observation random effect to control for extra-binomial overdispersion in the data.

We characterized the impact of annual water conditions and drought by considering our full 2000–2015 data set to include three sets of water years (year types): non-drought years 2000–2011 (2000, 2003–2006; 2010–2011), drought years 2000–2011 (2001–2002,

Figure 1.01. —Continued

2007–2009), and extreme drought (2013–2015). We considered a drought year to include any water year designated as "drought" or "critical" by the State of California Department of Water Resources. The State's criteria for "drought" or "critical" are based on the projected runoff (million acre feet) on 1 May (see http://cdec.water.ca.gov/cgi-progs/iodir/WSIHIST for details on the level for each classification and data access). We also considered all years combined 2000–2011 as the recent long-term average with which to compare with the 2013–2015 drought.

Because rainfall likely influences the extent of open water on the landscape, we evaluated models that included estimates of total precipitation. Rainfall data were taken from daily historic rainfall amounts recorded at weather stations via the NOAA National Climatic Data Center (www.ncdc.noaa.gov/cdo-web). To characterize rainfall across the Central Valley, we used data from one weather station in the northern and southern parts of the valley (Sacramento Metropolitan Airport and Fresno Yosemite International Airport) which had consistent temporal coverage across our study period. For each station, we calculated two- and four-week running totals then averaged these across stations. Precipitation data was then matched to the average date of the three main Landsat scenes covering the Central Valley for a given two-week period. Including precipitation in models allowed us to characterize the effect of recent localized rainfall in creating habitat, rather than broader scale water allocation decisions, and specifically if there were differences in the effect of rainfall across cover types. We hypothesized that agriculture cover types would be more likely to show a precipitation signature as there are many hectares that are not flooded July–May, whereas a larger fraction of managed wetlands are already flooded by mid-to-late winter (*Dybala et al., 2017*) when precipitation is expected to have its greatest impact.

To assess the impact of drought on private versus protected area wetlands, where differences might influence conservation and management strategies, we considered protection status as a single-factor in models and allowed an interaction with the year type. We derived protection status using the California Protected Areas Database (CPAD) (*GreenInfo Network, 2016*) overlaid on the habitat cover type layer to identify wetland cover types that fell within a protected area. The California Protected Area Database defines protected areas as those that are owned in fee and managed for open space purposes. Any cover types that fell outside of a protected area were assumed to be private or not protected. Since nearly all agriculture is on private land, we did not evaluate the influence of protection for models of rice, corn, or other crops.

To be able to better understand how within-year temporal availability of open water might differ among years in this dynamic system and given that interactions with smoothing terms (herein, day) are hard to include in GAMMs, we also fit separate GAMMs for each of the three year types (non-drought 2000–2011, drought 2000–2011, extreme drought 2013–2015) in each cover type with only a smoothing parameter of day. We plotted the model fitted values and 95% CI for each of the three data sets for each crop type to evaluate variation in the magnitude of the differences through the year. Covariates for precipitation and land protection were not included in these year type specific models.

Figure 1.01. —Continued

To characterize spatially variability in the impact of drought on wetlands, we compared the amount and timing of open water in seasonal wetlands between the Sacramento Valley Basin and San Joaquin Basin. We compared these two basins of the Central Valley because they have the most extensive managed wetlands and previous analyses have shown differences in the impact of drought between the two regions (*Reiter et al., 2015*). We fit separate GAMMs to seasonal wetland data from each basin that compared all three year-type groups (non-drought 2000–2011, drought 2000–2011, extreme drought 2013–2015).

Incentive programs

To quantify the relative contribution of the BirdReturns and WHEP habitat incentive programs, we calculated the proportion of the total estimated flooded rice habitat in the Sacramento Valley Basin that was provided by these programs. Specifically, we evaluated the contribution of fields that were flooded between July 2013 and May 2014 and again between July 2014 and May 2015. We compared the relative contribution of these programs to the habitat available in rice during the extreme drought (2013–2015) as a measure of the relative return on investment.

As the incentive programs largely focused on the Sacramento Valley basin and only in rice agriculture, we developed a GAMM of rice flooding using a subset of the data for that geography for the comparison (Fig. 1). We considered a combined model for the 2013–2015 data that included a smoothing term of day of the year relative to 1 July and an observation level random effect to account for overdispersion. We multiplied the daily model-fitted estimate of the proportion flooded by the estimated amount (ha) of rice planted in each year (216,105 ha in 2013 and 169,606 ha in 2014; *Dybala et al., 2017*) to get the area that was open water in each day. We then calculated the proportion of total habitat available per day provided by BirdReturns and WHEP in each of the year sets. Because the duration of flooding can influence the value of the habitat, we considered a metric "habitat ha days" for additional comparisons. Habitat ha days was the sum of all flooded ha across all days in the year. Each flooded ha on a day contributes one habitat ha day to the calculation.

To account for habitat remaining in rice fields upon termination of incentivized flooding, we used data from another study in rice to estimate the average duration that water remained in fields during the period that fields were drained (i.e., drawdown). These data are observations from fields visited two times per week until dry following the initiation of draining (Data S8). Water depth, the percent flooded, and the percent saturated was estimated for each field. We fit a GAMM to estimate the probability that an individual field would have waterbird habitat as a function of the days since the initiation of draining the field using observations from February to March in 2012 and 2013. We defined habitat as present in the observation data if fields had water depth >0 cm, or if fields were >0% flooded, or if fields were >50% saturated. Because field data included repeated visits to individual fields, we considered field as a random effect in the model. We multiplied the model fitted probability of habitat by day since draining was initiated with the amount of habitat when the draining started to estimate the daily amount of habitat remaining. We evaluated both a minimum estimate of habitat provided (assumes no habitat provided during drawdown following of end of practice) as well as the model corrected estimates.

Figure 1.01. —Continued

Table 1 Landsat 5 ETM and Landsat 8 OLI water classification model accuracy and bias for the Central Valley of California.

Satellite	Cover type	*N*	Accuracy	Bias
Landsat 8	Corn	2,237	0.95	0.05
Landsat 5	Corn	46	0.89	−0.07
Landsat 8	Rice	2,756	0.94	0.04
Landsat 5	Rice	640	0.89	0.03
Landsat 8	Other	1,005	0.99	0.001
Landsat 5	Other	475	0.96	0.003
Landsat 8	Freshwater emergent wetland	1,765	0.88	−0.11
Landsat 5	Freshwater emergent wetland	5,564	0.79	−0.01

Notes:

Accuracy (proportion correctly classified) and bias (average difference between the true and estimated probability of open water) of estimates of open water by different satellites (Landsat 5 ETM and Landsat 8 OLI) in three crop types (rice, corn, other crops [field crops, row crops, grain crops]) and managed wetlands (seasonal and semi-permanent).

Table 2 Adjusted-R^2 values for models of the proportion open water in three crop types and two managed wetland types in the Central Valley of California 2000–2015.

Model	Rice	Corn	Other	Seasonal	Semi-permanent
Day[1] + Year type[2]	0.62	0.28	0.15	0.79	0.56
Day + Year type * Protection[3] + Precip2wk[4]	0.63	0.29	0.15	0.79	0.59
Day + Year type * Protection + Precip4wk[5]	0.62	0.30	0.36	0.79	0.59
Day + Extreme drought[6]	0.63	0.29	0.14	0.79	0.56
Day + Extreme drought * Protection + Precip2wk	0.64	0.28	0.15	0.79	0.59
Day + Extreme drought * Protection + Precip4wk	0.62	0.30	0.36	0.79	0.59

Notes:

Generalized additive mixed models were fit to assess the proportion of open water in three crop types (rice, corn, other crops [field crops, row crops, grain crops]) and two managed wetland types (seasonal and semi-permanent). Adjusted-R^2 values indicate what proportion of the variance in the data was explained by the model. The protection variable was not included in crop type models.

[1] Day = indicator for day of the year between 1 and 319 starting as July 1 = 1.
[2] Year type = non-drought 2000–2011; drought 2000–2011; extreme drought 2013–2015.
[3] Protection = factor indicating whether the land is under protected status; not considered models of rice, corn or other crops.
[4] Precip2wk = total precipitation measured for two-weeks before the open water estimate from Landsat.
[5] Precip4wk = total precipitation measured for four-weeks before the open water estimate from Landsat.
[6] Extreme drought = factor indicating data from years 2013 to 2015.

Model fit and effect size

Overall, we evaluated relative model fit for each cover type and analysis using adjusted-R^2 and considered coefficients with $P < 0.05$ to be significant and $P < 0.10$ to be marginally significant. We characterized the effect size of covariates in our logistic GAMMs using the odds for individual effects (*Zuur et al., 2009*). Specifically, we calculated the percent change by of drought years over non-drought or average years 2000–2011 in our models as $(e^{Bxi} - 1) * 100$; where B_{xi} is the coefficient estimate for factor x, level i. All statistical analyses were completed using R v.3.3 (*R Core Team, 2017*) and the "gamm4" package (*Wood & Scheipl, 2014*).

RESULTS

Assessment of water classification models suggested some subtle differences in bias between our Landsat 5 and Landsat 8 derived data (Table 1). Overall, across cover types

Figure 1.01. —Continued

Table 3 Coefficient estimates (β) and model estimated percent annual change (%) in the proportion of open water in rice, corn, and other crops in the Central Valley of California 2000–2015.

		Rice			Corn			Other		
Model	**Covariate**	β	SE	%	β	SE	%	β	SE	%
1	Non-drought	−2.38	0.15		−2.97	0.11		−3.58	0.08	
	Drought	−0.14	0.23	−13	−0.21	0.17	−18	−0.14	0.13	−13
	Extreme drought	**−0.85**	**0.27**	**−57**	**−1.63**	**0.21**	**−80**	**−1.25**	**0.16**	**−71**
2	Non-drought	−2.57	0.16		−2.90	0.12		−3.62	0.09	
	Drought	−0.12	0.21	−11	−0.21	0.17	−19	−0.15	0.13	−13
	Extreme drought	**−0.67**	**0.29**	**−49**	**−1.71**	**0.22**	**−82**	**−1.22**	**0.17**	**−71**
	Precip two-weeks	**1.83**	**0.41**		*−1.08*	*0.65*		*0.51*	*0.31*	
3	Non-drought	−2.65	0.16		−3.04	0.13		−3.79	0.09	
	Drought	−0.09	0.22	−8	−0.20	0.17	−18	−0.11	0.14	−10
	Extreme drought	**−0.65**	**0.28**	**−48**	**−1.56**	**0.22**	**−79**	**−1.06**	**0.17**	**−65**
	Precip four-weeks	**1.10**	**0.32**		0.34	0.37		**1.12**	**0.17**	
4	Average	−2.44	0.12		−3.06	0.09		−3.64	0.07	
	Extreme drought	**−0.79**	**0.32**	**−54**	**−1.54**	**0.20**	**−79**	**−1.17**	**0.17**	**−70**
5	Average	−2.62	0.12		−2.99	0.10		−3.68	0.07	
	Extreme drought	**−0.62**	**0.27**	**−46**	**−1.62**	**0.21**	**−80**	**−1.17**	**0.17**	**−69**
	Precip two-weeks	**1.85**	**0.34**		*−1.07*	*0.65*		*0.51*	*0.31*	
6	Average	−2.69	0.14		−3.13	0.11		−3.84	0.07	
	Extreme drought	**−0.61**	**0.30**	**−45**	**−1.48**	**0.21**	**−77**	**−1.02**	**0.17**	**−64**
	Precip four-weeks	**1.01**	**0.35**		0.36	0.37		**1.13**	**0.17**	

Notes:
Coefficient estimates from generalized additive mixed models for drought 2000–2011 and extreme drought 2013–2015 should be interpreted relative to the intercept term of non-drought 2000–2011 (Models 1–3) and average 2000–2011 (Models 4–6). Estimates in bold were statistically significant with $P < 0.05$ and those in italics were considered marginally significant with $P < 0.10$.

the Landsat 8 model was more accurate. Among cover types, open water in freshwater emergent wetlands was predicted with the lowest accuracy by both satellites. Only in the case of corn did the directionality of the bias differ between the sensors. We used these cover type specific values to correct our observed estimates from each classification model.

Models for open water in rice, corn, and seasonal and semi-permanent wetlands were a good fit to the data based on residuals and explained 30–79% of the variance (Table 2). Models for other crops consistently explained relatively less of the variation. There were significant declines in open surface water during the recent extreme drought (2013–2015) in all cover types evaluated except for semi-permanent wetlands (Tables 3 and 4). In the agricultural landscape, the recent drought resulted in significantly less open water than the non-drought or average years; 45–57% declines in rice, 77–81% declines in corn, and 64–71% declines in other crops. However, after accounting for precipitation (two-weeks or four-weeks), which had a significant or marginally significant positive effect on open water in all crops (Fig. 2; Table 3), the difference between drought and non-drought years was typically less though still statistically significant (Table 3).

While seasonally flooded managed wetlands showed significant declines in open water in the recent drought compared to historic non-drought (47–58%) and average years

Figure 1.01. —Continued

Table 4 Coefficient estimates (β) and model estimated percent annual change (%) in the proportion of open water in seasonal and semi-permanent wetlands in the Central Valley of California 2000–2015.

		Seasonal			Semi-permanent		
Model	Covariate[1]	β	SE	%	β	SE	%
1	Non-drought	−1.02	0.10		−0.07	0.15	
	Drought	−0.01	0.16	−1	0.06	0.24	7
	Extreme drought	**−0.68**	**0.20**	**−49**	−0.34	0.30	−29
2	Non-drought	−0.93	0.12		0.24	0.17	
	Drought	−0.09	0.19	−9	0.15	0.26	17
	Extreme drought	**−0.93**	**0.23**	**−60**	−0.41	0.33	−34
	Protected	−0.13	0.15	−12	**−0.49**	**0.17**	**−39**
	Protected * Drought	0.16	0.20	17	−0.14	0.26	−13
	Protected * Extreme drought	**0.52**	**0.26**	**68**	0.03	0.34	2
	Precip two-weeks	−2.83	2.13		*−8.74*	*4.47*	
3	Non-drought	−0.97	0.14		0.16	0.18	
	Drought	−0.09	0.19	−8	0.16	0.27	17
	Extreme drought	**−0.90**	**0.23**	**−59**	−0.38	0.34	−32
	Protected	−0.13	0.13	−13	**−0.50**	**0.17**	**−40**
	Protected * Drought	0.16	0.20	18	−0.14	0.26	−13
	Protected * Extreme drought	**0.51**	**0.26**	**67**	0.04	0.35	4
	Precip four-weeks	0.83	1.65		0.28	2.36	
4	Average	−1.02	0.08		−0.04	0.12	
	Extreme drought	**−0.68**	**0.19**	**−49**	−0.36	0.30	−31
5	Average	−0.96	0.09		0.30	0.13	
	Extreme drought	**−0.89**	**0.22**	**−59**	−0.48	0.31	−38
	Protected	*0.45*	*0.24*	*57*	0.08	0.33	9
	Protected * Extreme drought	−0.07	0.10	−7	**−0.55**	**0.13**	**−43**
	Precip two-weeks	−2.81	1.67		−8.73	4.14	
6	Average	−1.01	0.10		0.22	0.14	
	Extreme drought	−0.87	0.22	**−58**	−0.44	0.32	−36
	Protected	*0.45*	*0.25*	*56*	0.09	0.33	10
	Protected * Extreme drought	−0.07	0.10	−7	**−0.56**	**0.13**	**−43**
	Precip four-weeks	0.81	1.55		0.27	2.31	

Notes:
Coefficient estimates from generalized additive mixed models for drought 2000–2011 and extreme drought 2013–2015 should be interpreted relative to the intercept term of non-drought 2000–2011 (Models 1–3) and average 2000–2011 (Models 4–6). Estimates in bold are statistically significant with $P < 0.05$ and those in italics $P < 0.10$.
[1] Protected * Drought and Protected * Extreme drought represent the influence of protected lands in drought and extreme drought years.

(49–59%; Table 4), changes in semi-permanent wetlands were not significant, though all estimates for drought variable coefficients were negative. Precipitation did not have a significant effect on managed wetlands, however, between 2000 and 2015 seasonal and semi-permanent wetlands had different amounts of open water with respect to protected areas during drought years. Semi-permanent wetlands had significantly less open water on protected land (~40%) compared to non-protected areas whereas seasonal wetlands had

Figure 1.01. —Continued

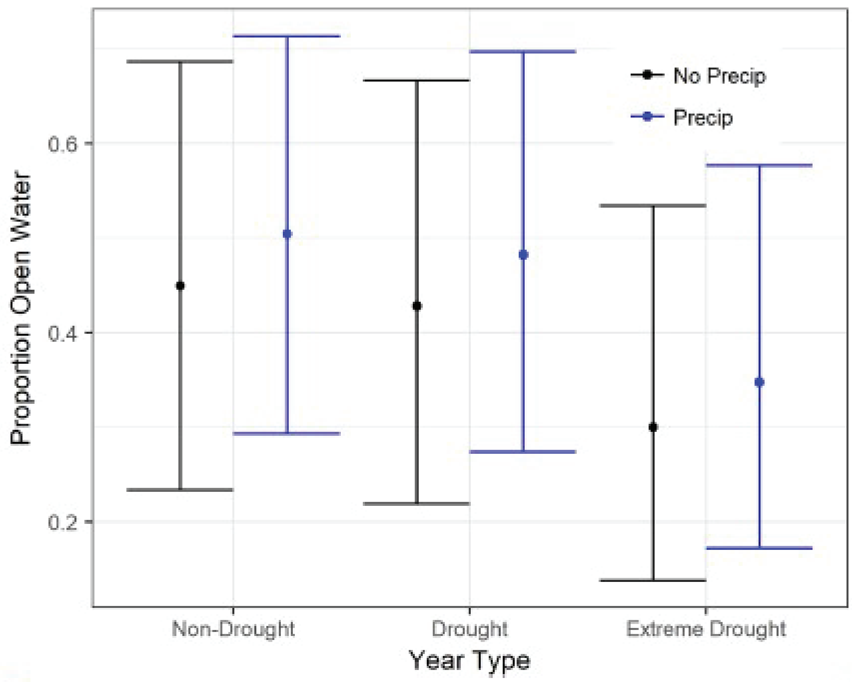

Figure 2 Estimated proportion open water in rice on 15 January in the Central Valley of California when accounting for precipitation. "No Precip" (black) assumes no rain falls in the previous four-weeks whereas "Precip" (blue) assumes average rainfall. Open water estimates were derived from generalized additive mixed models fit to all water distribution data from 2000 to 2015. Variables in the model included the amount of precipitation within four-weeks of the observed date, an indicator for drought years (2000–2011 and 2013–2015 (extreme drought), and a smoothing parameter for day of the year (July 1 = 1)). Fitted means are plotted with 95% confidence intervals.

Full-size DOI: 10.7717/peerj.5147/fig-2

marginally significant ($P < 0.10$) more open water on protected land (~56%) than on non-protected land (Table 4). The effects of protected land in wetlands appeared to be magnified during the recent drought with significant interactions detected between protection and extreme drought years compared to non-drought years 2000–2011 and all years 2000–2011.

Modeling year types separately emphasized the temporal differences in the timing and amount of water among years though was not used for statistical inference. In particular, it highlighted the period with the largest reductions in open water generally occurring across all cover types October through March (Figs. 3 and 4). Other crops were particularly reduced November to March while in corn there was substantially reduced water in nearly all months (Fig. 3). In rice, the recent drought reduced open water in February and March but also in April and May. In seasonal and semi-permanent wetlands, the reduction in water was largely observed between October and March (Fig. 4).

Figure 1.01. —Continued

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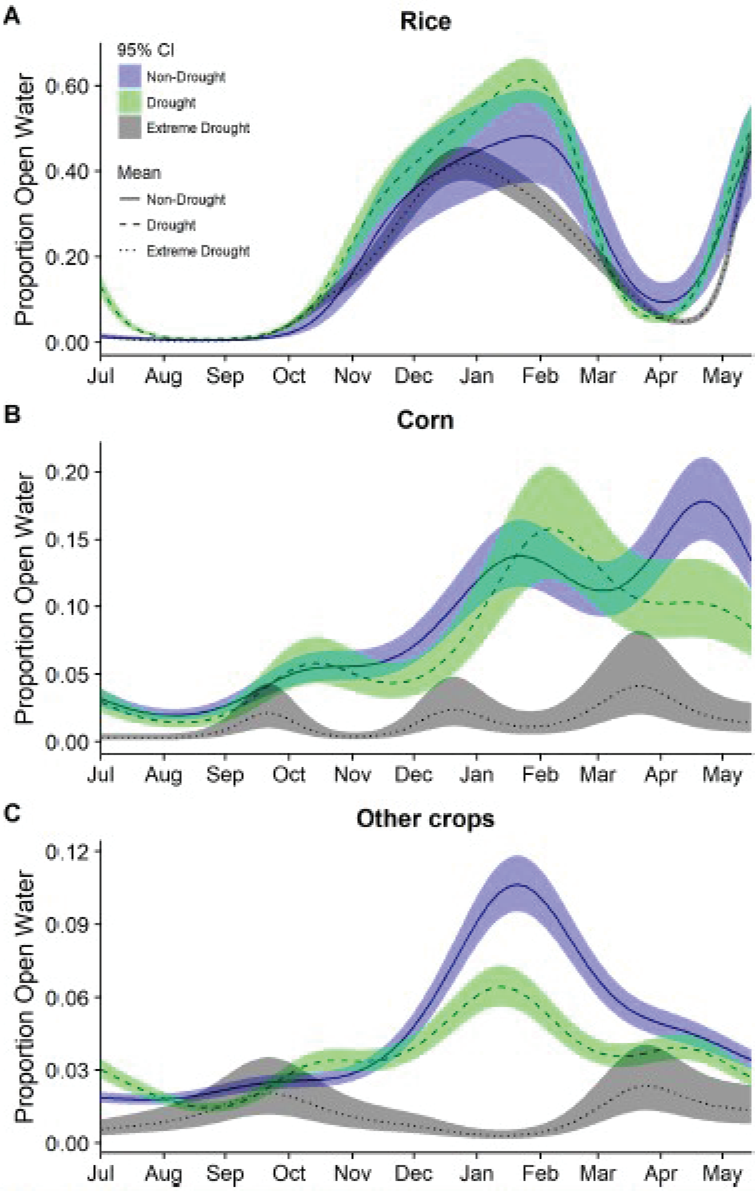

Figure 3 Estimated proportion of (A) rice, (B) corn, and (C) other crops that was open water in the Central Valley of California between 1 July and 15 May based on data from 2000–2011 and 2013–2015. Estimates were derived from separate models from separate generalized additive mixed models for each year group of non-drought 2000–2011, drought 2000–2011, and extreme drought 2013–2015. Models for each year group included only a smoothing parameter for day of year. Fitted means are plotted with 95% confidence interval bands. Full-size DOI: 10.7717/peerj.5147/fig-3

Figure 1.01. —Continued

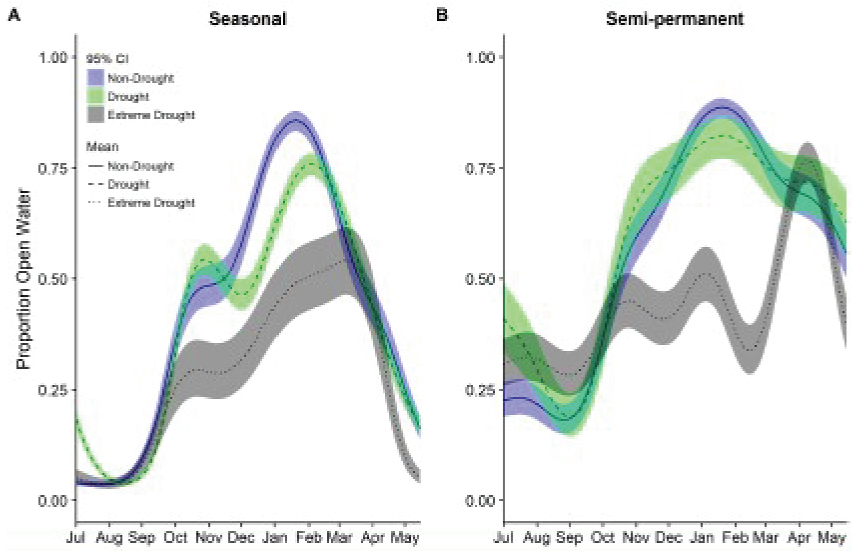

Figure 4 Estimated proportion of (A) seasonal and (B) semi-permanent wetlands that was open water in the Central Valley of California between 1 July and 15 May based on data from 2000–2011 to 2013–2015. Estimates were derived from separate generalized additive mixed models for each year group of non-drought 2000–2011, drought 2000–2011, and extreme drought 2013–2015. Models for each year group included only a smoothing parameter for day of year (July 1 = 1). Fitted means are plotted with 95% confidence interval bands. Full-size DOI: 10.7717/peerj.5147/fig-4

Patterns of seasonal wetland inundation differed between the Sacramento Valley Basin and the San Joaquin Basin, as did the impact of drought (Fig. 5). Seasonal wetlands in the Sacramento Valley overall have a higher proportion of open water and experienced, on average, 63–69% declines in open water during the 2013–2015 extreme drought while the San Joaquin Basin had declines of 85–86% (Table 5). Additionally, the San Joaquin Basin showed evidence of a lower but more prolonged peak in open water than the Sacramento Valley in both drought and non-drought years (Fig. 5).

The effect of incentive programs was noticeable when looking at flooding in rice in the Sacramento Valley (Fig. 6). The total area incentivized as part of BirdReturns in the region was 4,980 ha in spring 2014, 2,759 ha for fall 2014, and 1,357 ha for spring 2015 (*Golet et al., 2018*). Given the timing and duration of practices, this resulted in a minimum estimated total of 168,022 habitat ha days between 1 February and 4 April 2014 and, 85,666 habitat ha days between 1 September 2014 and 31 March 2015. WHEP incentivized 32,473 ha and 27,600 ha of habitat creation, respectively, in 2013–2014 and 2014–2015, which resulted in a minimum of 3.3 million habitat ha days (2013–2014) and 2.9 million habitat ha days (2014–2015) across the entire time period.

Our model to characterize presence of habitat during drawdown suggested that there was a significant negative effect of days since draining on the probability of habitat presence. However, there was a greater than zero probability of waterbird habitat for up to 30 days after the end of the incentivized practice and the initiation of draining.

Figure 1.01. —Continued

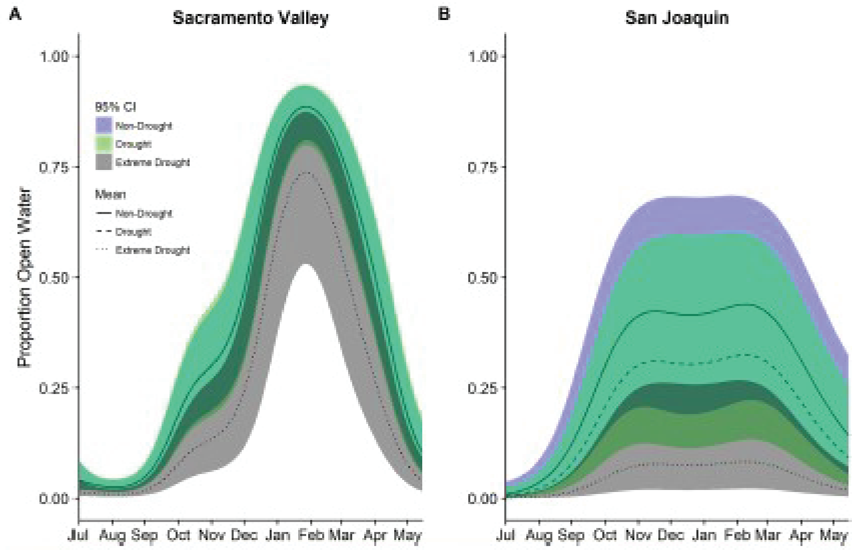

Figure 5 Estimated proportion of seasonal wetlands that was open water in the (A) Sacramento Valley Basin and (B) San Joaquin Basin of California 2000–2015. Estimates were derived separately for these two regions which have the largest amount of managed wetlands using a single model for each region and a factor for each year type: non-drought 2000–2011, drought 2000–2011, and extreme drought 2013–2015. A smoothing parameter for day of year (July 1 = 1) was also included in models. Fitted means are plotted with 95% confidence interval bands. Dark green areas represent overlap between confidence bands. Full-size DOI: 10.7717/peerj.5147/fig-5

Table 5 Summary of the proportion of open water in seasonal wetlands in the Sacramento Valley and the San Joaquin Valley in the Central Valley of California 2000–2015.

Region	R^2	Covariate	Estimate	SE	P	%
Sacramento	0.63	Non-drought	−1.41	0.20		
		Drought	−0.01	0.31	0.98	−1
		Extreme drought	**−1.02**	**0.43**	**0.02**	**−64**
San Joaquin	0.46	Non-drought	−1.48	0.37		
		Drought	−0.49	0.58	0.40	−39
		Extreme drought	**−2.16**	**0.70**	**0.01**	**−88**

Notes:
Adjusted-R^2, coefficient estimates (β), and estimated percent change in open water (%) from generalized additive mixed models are presented. Coefficient estimates from for drought 2000–2011 and extreme drought 2013–2015 should be interpreted relative to the intercept term of non-drought 2000–2011. Estimates in bold were statistically significant with $P < 0.05$.

This indicated the end of the incentivized period does not immediately end the habitat value. After accounting for a slow drawdown of water once the practices were complete by including our model-based estimates of proportion of remaining habitat for 30 days post-drawdown, BirdReturns provided an estimated total of 221,072 habitat ha days

Figure 1.01. —Continued

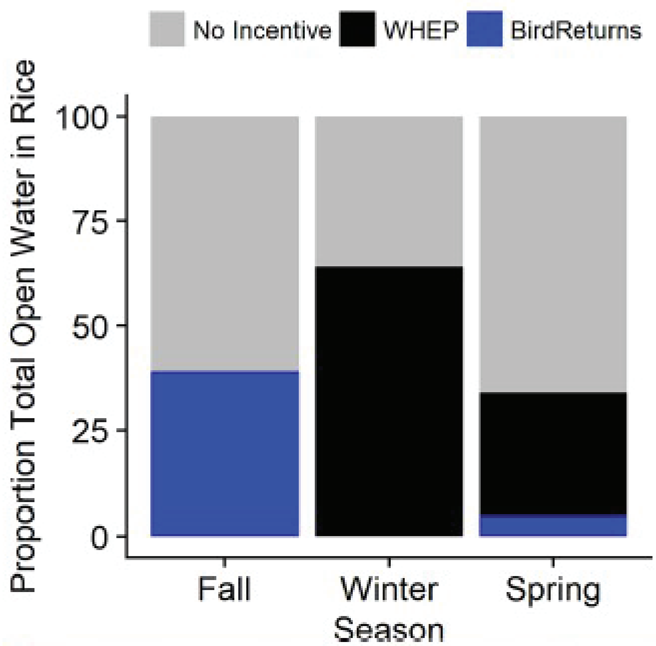

Figure 6 Estimated average daily percentage of open water in post-harvest rice provided by habitat incentive programs when active during the 2013–2015 extreme drought in the Central Valley of California. Incentive programs were The Nature Conservancy's BirdReturns and the Natural Resources Conservation Service's Waterbird Habitat Enhancement Program (WHEP). Three seasons evaluated for 2013–2015 were 1 September to 31 October (Fall), 1 November to 31 January (Winter), and 1 February to 4 April (Spring). Note: WHEP was only active 1 February to 7 March in late-winter and spring as fields were drained. Full-size DOI: 10.7717/peerj.5147/fig-6

occurring between 1 February and 4 May 2014 (adds 30 days to latest end date of practice) and 128,046 habitat ha days between 1 September 2014 and 30 April 2015, while WHEP provided an estimated 3.7 million habitat ha days in 2013–2014 and 3.1 million habitat ha days in 2014–2015. On days when the program was active between 1 September and 31 October 2014, BirdsReturns provided 14–61% (mean = 39%) of the daily waterbird habitat in flooded rice fields (Fig. 6). In the spring (2014: 1 February–4 May; 2015: 1 February–28 April), BirdReturns provided proportionally less habitat than in fall with on average 5% per day (min = 1%, max = 13%). When active, WHEP, on average, provided 64% (Min = 33%, Max = 100%) of the daily flooded rice in the winter (1 November to 31 January) and 29% (min = 15%, max = 46%) between 1 February and 7 March.

DISCUSSION

The extreme drought recently experienced in California impacted human, agricultural, and natural systems. Our study highlights that the drought caused a substantial reduction in open water habitats across the agricultural and wetland landscapes of the Central Valley and that the impact varied spatially and temporally. The observed decline ranged from

Figure 1.01. —Continued

approximately 20–86% depending on cover type, time of year, and region. Overall, post-harvest flooded rice declined less during the drought than flooded corn, other waterbird compatible crops, or seasonal wetlands. Further, seasonal wetlands in the San Joaquin Basin declined more than in the Sacramento Valley, confirming previous observations of spatial differences in the impact of drought across the Central Valley (*Reiter et al., 2015*).

The 2013–2015 drought reduced waterbird habitat over non-drought years more than previous droughts between 2000 and 2011, highlighting its severity. Estimates of open water for the 2013–2015 drought were lower than drought years between 2000 and 2011 across nearly all models and cover types. The length and severity of the recent extreme drought likely contributed to the observed decline as water restrictions were enacted and the cost of water began to increase (*Howitt et al., 2014*). More intensive modeling, however, is needed to tease out these policy and socio-economic drivers of changes in water applied to the landscape.

Mid-winter or peak flooding (November to February) appeared most affected across cover types. Fall, which is generally the driest time of the year (*Reiter et al., 2015*) and already a period of habitat limitation for migratory shorebirds (*Dybala et al., 2017*), remained dry across cover types evaluated, but did not show particularly significant reductions in open water during the drought. The flooding pattern was similar in spring, however open water in post-harvest rice declined very quickly and was particularly low March through May during the 2013–2015 drought compared to other drought and non-drought years. Open water in rice during April and May, which is associated with the planting of the rice crop, was also delayed during the drought, supporting previous findings of drought impacts on open water and exacerbating the mismatch in the timing of habitat for migratory birds (*Schaffer-Smith et al., 2017*). Overall open water in post-harvest rice experienced smaller declines compared with other crop types and seasonal wetlands. While this is consistent with previous work that highlights the resilience of the Sacramento Valley surface water compared to other regions (*Reiter et al., 2015*), our results also suggest that a large fraction of the open water in rice (up to 100% of observed) during certain times of the year, particularly fall and winter, may have been provided through incentive programs.

The value of incentive programs to generate habitat and ecosystem services in the Central Valley has been documented (*Duffy & Kahara, 2011*; *DiGaudio et al., 2015*; *Golet et al., 2018*), yet this is the first regional-scale assessment of the effectiveness and additionality of incentive programs in providing wetland habitat during drought and further underscores the contribution of these programs. BirdReturns was particularly effective at providing habitat in fall; a period that is already thought to be food limiting for migratory shorebirds (*Dybala et al., 2017*). Fields enrolled in BirdReturns during in fall 2014 had some of the highest shorebird densities ever reported for agriculture in this region, confirming this to be a time of habitat deficit (*Golet et al., 2018*). The WHEP was effective during the period of peak flooding when nearly 70% of available flooded rice habitat was provided by the program. However, it is not known what proportion of those individual farmers who enrolled in either BirdReturns or WHEP would have adopted the enhancement practices even if the incentive payments were not available (*Baumgart-Getz,*

Figure 1.01. —Continued

Prokopy & Floress, 2012; *Reimer et al., 2014*). Further assessment is needed to know how much the incentive programs directly offset the impact of drought in post-harvest rice or simply supplemented funding for activities that might have been done regardless.

Our analysis highlights that recent localized precipitation can help supplement the open water habitat in agriculture that is largely created through intentional diversions of snow melt from the surrounding mountain ranges (*Central Valley Joint Venture (CVJV), 2006*; *Hanak & Lund, 2012*; *Golet et al., 2018*). The strong positive effect of precipitation was most noticeable in agricultural cover types and particularly in rice. Some of the reduced flooding in rice in the recent drought compared to non-drought years may be the result of less rain or potentially less saturated soils from intentional flooding that can become open water with additional rainfall. While much of this precipitation-driven water detected using satellites, we assume, may be too shallow for most waterfowl (particularly ducks), it certainly has value for shorebirds, wading birds, and other freshwater dependent taxa (*Strum et al., 2013*). Further research is needed to determine the overall contribution to habitat of rain flooded agricultural fields and consequently how incentive programs may vary in effectiveness in wet versus dry years. However, our results also highlight that among year variation in habitat availability due to year type (drought versus non-drought) likely plays a bigger role in the amount and timing of habitat than within Central Valley precipitation.

While habitat availability appeared to decline substantially during some points of the year in certain cover types, our analysis does not directly assess the potential impacts to the wildlife that rely on these systems. Recent work by *Petrie et al. (2016)* indicated that the drought in the Central Valley could have had significant impacts on waterfowl populations. They used expert opinion to develop drought scenarios and a bioenergetics model to determine impact to waterfowl from a food energy perspective. The scenario they developed assumed a 25% decline in flooded wetlands in 2014–2015. However, our satellite and model derived estimates for the same period suggest a much more severe impact of the drought on wetlands than was assumed by *Petrie et al. (2016)*. Parameterizing their bioenergetics model with data from this study could help to further illuminate the species and population level impacts of the drought. Similarly, a recently developed bioenergetics model for shorebirds could further assess the impacts of drought on these species which rely on open water cover types in wetlands and flooded agriculture (*Dybala et al., 2017*). However, integrating our data with bioenergetics models for waterfowl or shorebirds will require the development of two additional parameters for drought not evaluated here: changes in wetland moist soil seed productivity for waterfowl (*Naylor, 2002*) and changes in water depth profiles for shorebirds (*Dybala et al., 2017*).

Open water in seasonal wetlands declined significantly during the recent drought in both the Sacramento Valley and the San Joaquin Basin. However, the peak proportion of open water was higher in seasonal wetlands in the Sacramento Valley Basin and declined less during drought compared with the San Joaquin Basin. This spatial difference may be in part explained by the fact that seasonal wetlands on protected land had a higher proportion of open water than non-protected, largely private, seasonal wetlands during the recent extreme drought; a larger proportion of the managed wetlands in the San

Figure 1.01. —Continued

Joaquin Basin are privately owned compared to the Sacramento Valley. Beyond speculating on the observed patterns, we were unable to evaluate why there may have been differences in the impact of drought in seasonal wetlands based on protection status. Further complicating interpretation was the finding that semi-permanent wetlands had an opposite pattern with lower open water in protected wetlands.

We also quantified differences in the timing of open water in seasonal wetlands between the Sacramento Valley Basin and the San Joaquin Basin with the peak proportion of open water occurring earlier and remaining on the landscape longer in the San Joaquin Basin (November to March) compared to the Sacramento Valley (end of November to early March). While we do not know the exact cause of these different patterns, recent studies of overwintering shorebirds in the Central Valley suggest that shorebirds in the more hydrologically dynamic Sacramento Valley move longer distances and migrate out of the area significantly more than birds in the San Joaquin Basin (*Barbaree et al., 2018*). Differential patterns of wetland inundation may be driving some of these observed differences in movement ecology. Incorporating different flooding patterns among regions of the Central Valley into bioenergetics models (*Petrie et al., 2016*; *Dybala et al., 2017*) could inform strategies of how to maximize the value of the habitat created across the whole landscape for waterfowl and shorebirds.

CONCLUSION

Our study highlights the negative impacts that extreme drought can have on essential wetland and agricultural waterbird habitats in the Central Valley of California but also the substantial benefits that can be provided through habitat incentive programs. Climate change models and habitat projection scenarios for California indicate the strong likelihood of increasing temperatures and more, potentially extreme, variation in precipitation patterns (*Snyder, Sloan & Bell, 2004*; *Matchett & Fleskes, 2017*). With more limited water resources, our results suggest that wetland managers will need to be ever more strategic in how they allocate incentive program water to prevent the reductions observed in the recent extreme drought. Furthermore our assessment provides a novel perspective of the impacts of extreme drought in the Central Valley and points to the need to have dynamic strategies (*Reynolds et al., 2017*) to provide more resilient habitat in flooded agriculture and wetlands during early to late winter, in the face of additional, and potentially more extreme, drought events. Lastly, we conclude that remotely sensed data can be a powerful tool to track water in the Central Valley and should be harnessed to regularly update water and wetland managers on how much habitat is available and where, so that there can be more coordinated data-driven water management. While many sophisticated models of water scenarios can be evaluated (*Draper et al., 2003*; *Yates et al., 2009*), understanding where water and wetland habitats are ultimately distributed on the landscape in space and time is needed for water managers to make decisions that maximize the value of limited water resources for wildlife (*DWR, 2009*).

Figure 1.01. —Continued

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ADDITIONAL INFORMATION AND DECLARATIONS

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Competing Interests

The authors declare that they have no competing interests. Matthew E. Reiter, Nathan K. Elliott, and Dennis Jongsomjit are employees of Point Blue Conservation Science, and Gregory H. Golet and Mark D. Reynolds are employees of The Nature Conservancy.

Author Contributions

- Matthew E. Reiter conceived and designed the experiments, performed the experiments, analyzed the data, contributed reagents/materials/analysis tools, prepared figures and/or tables, authored or reviewed drafts of the paper, approved the final draft.
- Nathan K. Elliott performed the experiments, analyzed the data, contributed reagents/materials/analysis tools, prepared figures and/or tables, authored or reviewed drafts of the paper, approved the final draft.
- Dennis Jongsomjit performed the experiments, analyzed the data, contributed reagents/materials/analysis tools, authored or reviewed drafts of the paper, approved the final draft.
- Gregory H. Golet conceived and designed the experiments, contributed reagents/materials/analysis tools, authored or reviewed drafts of the paper, approved the final draft.
- Mark D. Reynolds conceived and designed the experiments, authored or reviewed drafts of the paper, approved the final draft.

Figure 1.01. —Continued

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Data Availability

The following information was supplied regarding data availability:

The raw data and R-code are provided as Supplemental Files.

Supplemental Information

Supplemental information for this article can be found online at http://dx.doi.org/10.7717/peerj.5147#supplemental-information.

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Figure 1.01. —Continued

Appendix 2. Odds of Water or Dry Classification by Duck Activity

Proportion of duck telemetry locations in the Central Valley (California) listed by biological activity during January 2015–September 2018 that were classified as in water or on dry land using the dynamic open-water dataset (table 2.1).

Table 2.1. Proportion of duck telemetry locations in the Central Valley, California, by biological activity during January 2015–September 2018 that were classified as in water or on dry land using the dynamic open-water dataset.

[%, percent]

Biological activity[1]	Dry (%)	Water (%)	Odds of being in water[2]
Feeding, roosting	27.7	62	2.2
Nesting	2.3	0.4	0.2
Raising brood	0.8	1	1.3
Molting	2	3.5	1.8
Average	0.8	1	1.3

[1]Most Feeding and roosting locations occurred during the wintering period and before migration to breeding areas. Nesting, raising brood, and molting locations were recorded during the breeding season. A small proportion of additional locations (less than 1 percent not shown in the table) were assessed to occur during flight and were not necessarily representative of use of land cover by ducks.

[2]Odds equals percent as water/percent as dry land.

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