SAN FRANCISCO
ESTUARY & WATERSHED SCIENCE
Sponsored by the Delta Stewardship Council and UC Davis Institute of the Environment

RESEARCH

Bird Habitat Value and Management Priorities of the California Winter Rice Habitat Incentive Program

Sarah H. Peterson*[1], Joshua T. Ackerman[1], Carley R. Schacter[1], C. Alex Hartman[1], Mark P. Herzog[1]

ABSTRACT

Flooding rice (*Oryza sativa*) agricultural fields during winter to facilitate rice straw decomposition has mitigated the loss of some of the natural wetlands in California's Central Valley. We conducted bird surveys in 253 rice checks (2,158 ha) within 177 rice fields in the Sacramento Valley during the fall and winter of 2021–2022 and 2022–2023 to evaluate factors that influence bird use of winter-flooded, post-harvest rice fields enrolled in the California Winter Rice Habitat Incentive Program. We counted 143,932 birds from 57 species, including dabbling ducks (86.4%), geese (8.0%), shorebirds (0.9%), wading birds (0.7%), and other birds (4.0%). Extrapolating from the lowest densities observed in rice fields during the 70-day mandatory flooding period, we estimated that properties enrolled in this public–private partnership provided habitat for at least 271,312 birds day^{-1} (16,248 ha; 2021–2022) and 147,315 birds day^{-1} (8,448 ha; 2022–2023), totaling > 10 million bird-use-days each winter. Water depth had the greatest influence on bird abundance and diversity. Relatively shallow water depths (≤ 13 cm) had greater abundance of geese, shorebirds, and wading birds, and higher diversity, whereas intermediate depths (~23 cm) resulted in the greatest dabbling duck abundance. Duck, goose, and wading bird abundances were greatest—and species richness and family diversity were highest—8 days after the onset of flooding in rice fields (typically late October), followed by a decline in bird use until 65 to 87 days post-flooding, after which bird use increased slightly. Bird abundance and species diversity were lowest in rice fields with the greatest hunting intensity (≥ 3 days week^{-1}). We identified several habitat variables that could be managed and prioritized by landowner incentive programs to increase bird use of winter-flooded rice, including water depth, variation in emergent vegetation height, mudflat habitat availability, rice check shape, hunting intensity, and post-harvest treatment of residual rice straw.

SFEWS Volume 22 | Issue 3 | Article 3
https://doi.org/10.15447/sfews.2024v22iss3art3

* Corresponding author: sepeterson@usgs.gov

1 US Geological Survey
Western Ecological Research Center
Dixon Field Station
Dixon, CA 95620 USA

KEY WORDS

bird diversity, Central Valley, rice agriculture, rice field, shorebird, water depth, water management, waterbird, waterfowl, working lands

INTRODUCTION

The Central Valley of California is an important overwintering area for waterfowl, shorebirds, and wading birds, collectively described as waterbirds (Shuford et al. 1998; CVJV 2020). More than 90% of the historic natural wetlands in the Central Valley have been lost to agricultural development and water diversion (Heitmeyer et al. 1989; Dahl 1990; Wilen and Frayer 1990), and large-scale landscape changes within the Central Valley have directly affected the distribution, habitat use, and movements of waterfowl (Fleskes et al. 2005; Ackerman et al. 2006). The practice of flooding rice (*Oryza sativa*) agricultural fields during winter has mitigated some of the natural wetland loss in the Central Valley by providing alternate seasonal wetland habitat (Day and Colwell 1998; Elphick and Oring 1998; Elphick 2000). Typically, close to 200,000 ha of rice are planted annually in the Central Valley, with more than 95% occurring in the northern Sacramento Valley (Strum et al. 2013; Shuford and Dybala 2017; CVJV 2020; USDA Crop Acreage Data, *https://www.fsa.usda.gov*). Rice farmers historically burned residual rice straw after harvest in the fall; however, since the implementation of the California Rice Straw Burning Reduction Act (AB 1378 in 1991) to reduce greenhouse gas emissions and improve air quality, many farmers instead flood their rice fields in the fall and winter to facilitate decomposition of rice straw (Miller et al. 2010; Garr 2014). These winter-flooded rice fields, which can total 140,000 ha in some years, have been shown to provide high-value waterbird habitat, with plant and invertebrate food densities similar to natural wetlands (Gilmer et al. 1982; Elphick 2000; Fleskes et al. 2012; Strum et al. 2013). Use of winter-flooded rice fields by waterfowl also directly benefits rice farmers because waterfowl foraging can increase the decomposition rate of residual rice straw and may also reduce insect and weed pests (Bird et al. 2000).

The California Department of Fish and Wildlife's California Winter Rice Habitat Incentive Program (Assembly Bill 2348, Section 3469 of the Fish and Game Code) was established in 2018 to provide monetary incentives to landowners who agree to flood their rice fields for 70 continuous days between October 15 and March 15, and to manage their property according to a management plan developed by biologists in the California Department of Fish and Wildlife Wetland Conservation Program. This public–private partnership can be beneficial to both landowners and wildlife; private landowners receive monetary compensation and wildlife may benefit through greater habitat availability. Building mutually beneficial partnerships between public management agencies and private landowners (Brasher et al. 2019), such as those in the California Winter Rice Habitat Incentive Program, can help future conservation efforts to maintain the existing populations of waterfowl and waterbirds.

More than 8.5 million waterfowl and half a million shorebirds use the Central Valley during the winter (Shuford et al. 1998; Ackerman et al. 2014; Skalos and Weaver 2020), and rice fields provide a large proportion of the wintering wetland habitat for waterbirds, including substantial food resources (Miller 1987; Stafford et al. 2010; Petrie et al. 2016; Dybala et al. 2017; Shuford and Dybala 2017). Managed flooding of rice fields during winter increases their suitability for most waterbirds, resulting in greater densities, species richness, and conservation value in flooded rice fields than in dry rice fields (Day and Colwell 1998; Elphick and Oring 1998; Elphick and Oring 2003; Strum et al. 2013). Winter-flooded rice fields in the Central Valley are located entirely within the Sacramento and Yolo–Delta Planning Regions, as defined by the Central Valley Joint Venture (CVJV) partnership (led by the US Fish and Wildlife Service; CVJV 2020). Within the Sacramento Planning Region, which contains 95% of all winter-flooded rice habitat in the Central Valley, approximately 81% of wintering waterfowl habitat and 74% of food energy is thought to be provided by winter-flooded, post-harvest rice fields (CVJV 2020). Winter-flooded rice fields and the checks within each field can vary in size and shape, water depth, hunting intensity, availability of mudflat habitat, prevalence and height of emergent vegetation, and post-harvest rice treatments, which in turn may influence the abundance and species composition of waterbirds that use each field. The timing of when rice fields are flooded in the fall and the duration of flooding through the winter can have an important influence on the availability of wintering habitat for birds in the Central Valley. Rice fields that are flooded earlier in the fall may provide important habitat when other flooded habitats are less available in the Central Valley (Donnelly et al. 2022). The individual quality of winter-flooded rice fields for foraging granivorous waterbirds may decrease between flood-up, when seed resources are first made available, and late winter, when seeds have been consumed or decomposed (Greer et al. 2009). At the same time, bird abundance and species composition in the Central Valley are changing seasonally and depend on the size of local breeding populations (Ackerman et al. 2014) and the timing of migration by overwintering birds (Fleskes et al. 2018; Donnelly et al. 2022).

Water depths within individual rice fields are relatively uniform, and depth has been shown to be one of the most important predictors of species composition (although not density) among rice fields (Elphick and Oring 1998). Shorebirds are typically found in shallower water (3–13 cm), dabbling ducks at intermediate depths (14–22 cm), and diving ducks in deeper water (24–33 cm), with the greatest overall number of species occurring in rice fields with water between 15 and 20 cm deep (Elphick and Oring 1998; Dybala et al. 2017).

Post-harvest treatment of rice fields conducted by farmers in the fall may also influence waterbird use of those fields in the winter. Post-harvest treatment practices can include removal of residual straw (baling), breaking the residual straw into smaller pieces to increase decomposition rates (e.g., chopping), and/or incorporating residual straw into the soil (e.g., stomping, discing). Post-harvest treatments that leave more waste rice grain accessible to foraging birds are predicted to increase the abundance of highly granivorous waterbirds, such as waterfowl (Miller 1987; Stafford et al. 2010). As an example, more dabbling ducks were found in non-baled than baled fields (Sesser et al. 2016). Additionally, incorporation of straw residues into the soil can promote invertebrate populations (Lawler and Dritz 2005), and densities of small shorebirds (primarily invertebrate feeders) were greatest in rice fields where straw was incorporated into the soil (Elphick and Oring 1998). Some treatments, such as discing, leave large clods of dirt throughout the plowed field, which may ultimately reduce the availability of rice seeds to foraging granivores (Garr 2014; Matthews 2019).

Given the importance of winter-flooded rice fields to waterbirds in the Central Valley, identifying habitat variables that can be managed and used to prioritize enrollment of candidate properties to best promote waterbird use and diversity could increase the effectiveness of the California Winter Rice Habitat Incentive Program. We quantified bird use of rice fields in the Sacramento Valley that were enrolled in the California Winter Rice Habitat Incentive Program, especially dabbling ducks, shorebirds, wading birds, and geese. Specifically, we evaluated the effects of a variety of habitat and management variables associated with rice farming—including water depth, vegetation height, post-harvest treatment, and hunting intensity—on overall bird abundance, abundance of different taxonomic guilds, and bird diversity.

MATERIALS AND METHODS

We surveyed winter-flooded, post-harvest rice fields within the Sacramento Valley, California (Figure 1) from October 13, 2021 through February 14, 2022 and December 8, 2022 through February 6, 2023. Because many landowners were unable to obtain water to flood their fields under the extreme drought conditions during these years, there was limited enrollment in this study by landowners (coordinated by the California Department of Fish and Wildlife's Wetland Conservation Program) and a staggered timing of flood-up during the fall and winter of 2021–2022 and 2022–2023. Thus, we were unable to develop and implement an *a priori* randomized sampling scheme. Instead, we spatially and temporally varied the order of surveys as enrolled rice fields became available for survey, with the intent to avoid sampling the same geographical area on

https://doi.org/10.15447/sfews.2024v22iss3art3

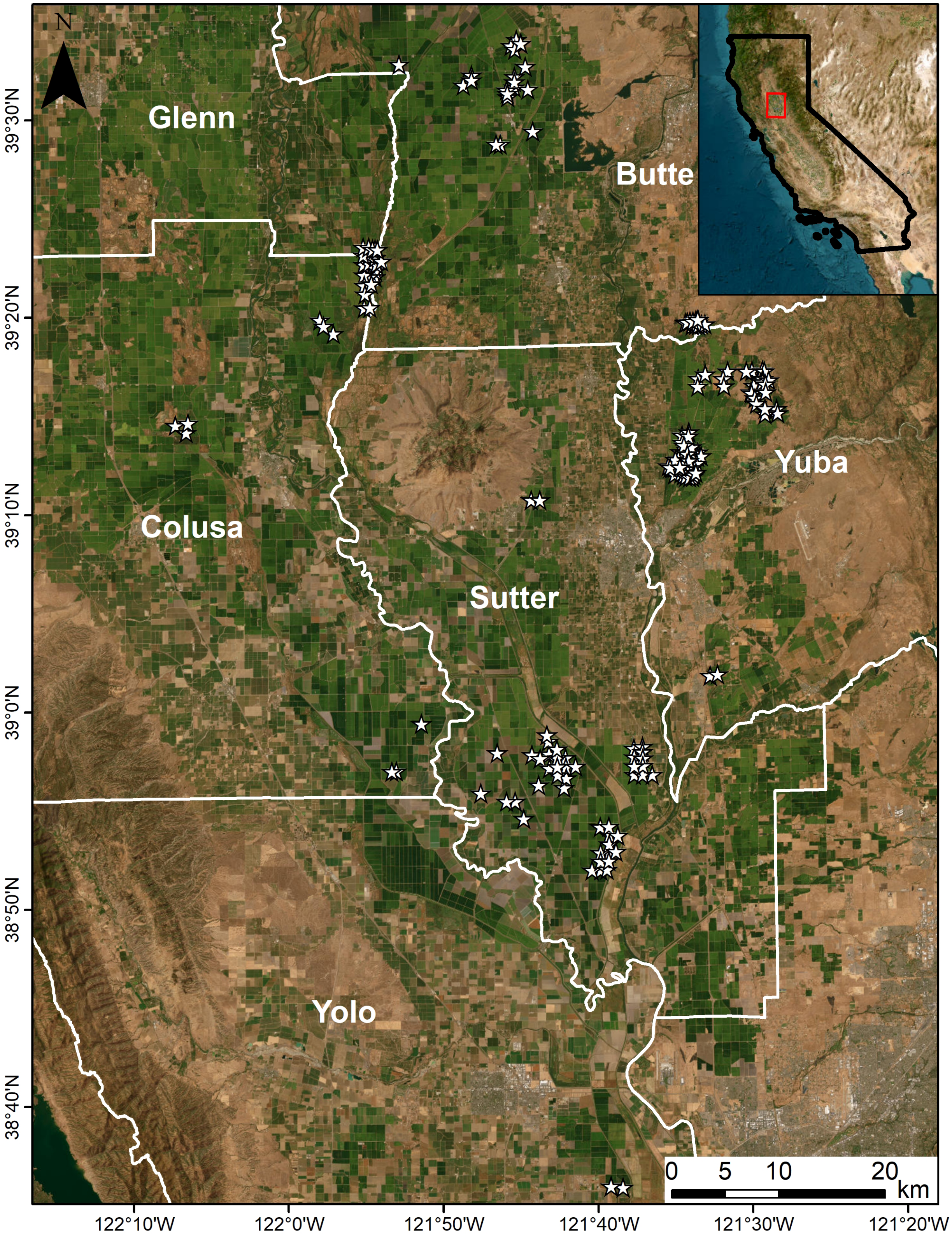

Figure 1 Locations of rice fields (*stars*) surveyed for waterbird use within the Sacramento Valley, California, during the winters of 2021–2022 and 2022–2023. Counties are labeled in *white*. The *inset map* outlines California in *black* and delineates the main map in *red*. Background imagery source: ESRI, Maxar, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community.

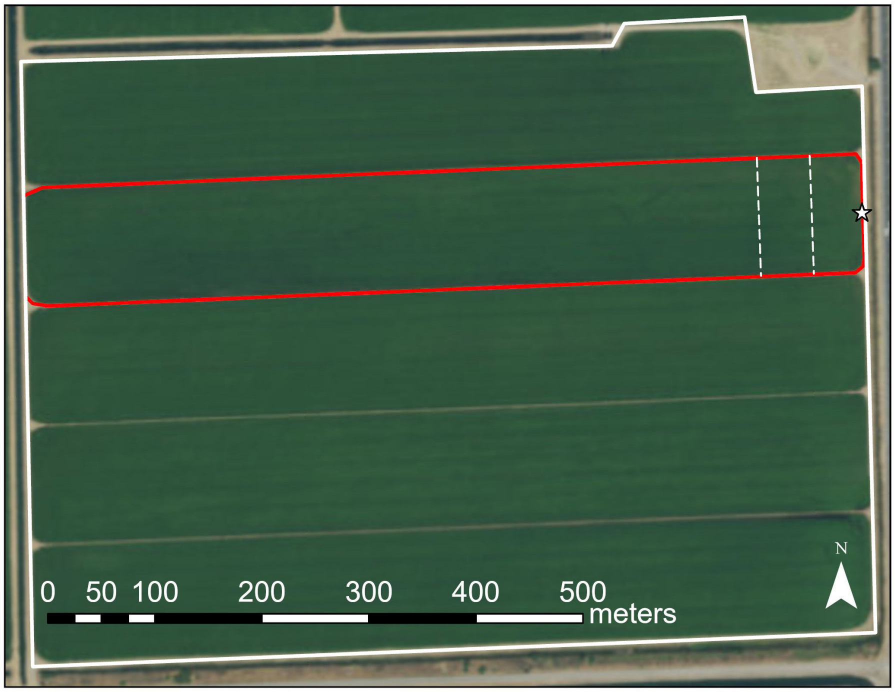

Figure 2 An example of a randomly selected rice check (*red outline*) within a rice field (*white outline*). We conducted bird surveys and overall habitat assessments from an observation point on the short end of the check (*white star*), and walked habitat transects (*dashed white lines*) every 50 m from the observation point, taking habitat measurements every 5 m until we had a minimum of 25 transect data points in each rice check. Background imagery source: USGS The National Map.

consecutive days as much as possible. Rice farms in the Sacramento Valley are organized into separate rice fields, and each field consists of multiple smaller rice checks of varying sizes that share the same water conveyance (Figure 2). Each rice check is leveled and surrounded by earthen levees. We randomly selected one to three rice checks within each individual rice field to survey. Within the dataset of 177 sampled rice fields, 68% had only one rice check sampled, and no more than three rice checks were sampled from the same field during the same year, although 2% of rice fields had four to six rice checks sampled in total between the 2 years because of the overall California drought and the limited opportunities to survey other rice fields (see "Statistical Analysis").

Rice field sampling consisted of (1) a bird survey that was followed by (2) an overall habitat assessment, and (3) a more detailed habitat transect survey, each of which is described in detail below. Because the habitat transect survey required surveyors to physically enter the rice checks and could disturb the birds, they were always conducted after the completion of all bird surveys in the area on a given day. Habitat assessments and transect surveys were done on the same day as bird surveys for 99% of surveys, and on three occasions were completed within 5 days after the bird survey as a result of weather or time constraints. Conducting the habitat assessment on the same day as—or no later than 5 days after—the bird survey, ensured that the habitat assessment accurately reflected the conditions (especially water levels) of the rice check at the time of the bird survey.

BIRD SURVEYS

The first bird survey of the day began approximately 30 min after sunrise, and we began the last survey of the day no later than 12:00 (98.0% of bird surveys began before 11:00). We postponed or excluded bird surveys if weather conditions did not meet minimum requirements for visibility and consistency as a result of: (1) heavy rain and/or sustained winds > 20 mph, (2) heavy fog, (3) < 50% of the check was sufficiently visible to conduct an accurate bird count, (4) disturbance due to hunting or other human activities, or (5) the randomly selected check was not actually flooded upon our arrival (we surveyed only flooded rice fields).

https://doi.org/10.15447/sfews.2024v22iss3art3

During each bird survey, we first identified an observation point on the short side of the rice check (Figure 2), where a single observer using binoculars and a spotting scope could record all birds (except songbirds) observed within the rice check. We set no minimum or maximum duration for bird surveys to be completed, but we made every effort to complete the bird survey as quickly as possible to limit the potential for double counting. Because waterfowl are easily disturbed, which often results in them flushing and moving away from the area, we first conducted a count from as far away from the observation point as possible. During this first count, we counted and identified birds to the lowest taxonomic level possible. We then moved closer to the field and to our final observation point where we performed the bird survey again to revise our count and confirm species identification. If birds flushed during the count, we counted bird numbers in the air and assigned them the behavior they were doing before being flushed (if known). When possible, observers remained within the vehicle during the survey to minimize bird disturbance.

We considered a bird to be associated with the surveyed rice check if it was in the water or on the ground within the check, standing on levees surrounding the check, perched within 50 m of the check (only for raptors, corvids, and Belted Kingfisher [*Megaceryle alcyon*]), flying < 100 m over the water to forage (e.g., terns, Belted Kingfisher) or evaluate the area (e.g., ducks), or circling > 100 m above the check (only for raptors and corvids). We did not include birds in the air > 100 m that were in transit across the rice check. For each observation (individual bird or group of similar birds), we recorded: (1) time, (2) species, (3) number of birds, (4) sex (if possible), (5) behavior when first observed (described below), and (6) microhabitat within a 3-m radius of the bird (described below). For large flocks, it was not practical to record all data separately for each individual. Instead, we conducted scan sampling to record details for representative subsets of the group, and then used those percentages to estimate the composition of the flock. For example, a flock of 1,000 Northern Pintail (*Anas acuta*) could be recorded as 25% feeding and 75% roosting, and 50% male and 50% female. If we could not determine the species, we identified birds to the lowest taxonomic level possible (e.g., Least/Western Sandpiper [*Calidris* spp.], duck, gull). We also noted if a male and female were clearly associated as a pair.

We classified microhabitat within 3 m of the bird based on substrate (water, mud, or dry ground) and emergent vegetation (bare/unvegetated, residual rice, or non-rice vegetation). Other possible microhabitat categories included: structure (standing on man-made structure or tree), field levee (standing on larger, more permanent outer field boundaries), and check levee (standing on smaller, more temporary internal boundaries between rice checks). Birds that flushed before the microhabitat could be determined or were flying over the check were not assigned to a microhabitat. We classified bird behavior into the following categories: feeding (feeding or searching for food, including swim feeding and aerial foraging), roosting (resting, preening, or standing), swimming (not feeding), walking (not feeding or engaged in any other behavior), flying (< 100 m over the rice check, not feeding), breeding (alarm calling, copulating or engaged in pre- or post-copulatory display), flyover (> 100 m over the rice check; for raptors and corvids only), and flushed (used only if behavior before flushing was unknown).

We estimated the distance between each bird or the center of a flock and the nearest levee using rangefinders (Ranger 1800, Vortex Optics, Barneveld, WI) and the known dimensions of each rice check from a GIS (ArcMap 10.6.1; Environmental Research Systems Institute, Redlands, CA). At the end of the survey, we estimated the percentage of each rice check that was not surveyed as a result of thick vegetation or extreme distance.

HABITAT ASSESSMENT

We visually estimated habitat variables that characterized each rice check overall. We estimated the proportions of each combination of substrate (water, mud, or dry), emergent vegetation (bare, rice, or non-rice vegetation), and the presence of visible dirt clods (above the water line if in water). For example, 80% water/bare/no dirt clods and 20% mud/rice/no dirt clods denoted a rice check where 80% of the area comprised open water with no emergent vegetation (bare) and no dirt clods, and 20% of the area comprised muddy substrate with emergent residual rice and no dirt clods. We counted the number of perch sites (e.g., trees, fence posts, telephone poles) available to raptors within 50 m of the rice check's edge to examine if there were more potential waterbird avian predators as the number of perches increased.

After all surveys were completed, we obtained the following information about each rice field from landowners and managers: (1) date when flooding started, (2) post-harvest treatment(s), and (3) frequency of hunting. We categorized post-harvest treatments into one of four groups:

1. Rice straw mechanically broken up but left in the field and not incorporated into the soil substrate (e.g., chopping; 3.6% surveys; in figures as 'Broken');

2. Residual rice straw or stubble incorporated into the soil substrate (e.g., stomping or rolling; 12.2% of surveys; in figures as 'Incorporated');

3. Residual rice straw both broken up and incorporated into the soil (e.g., chiseling or discing; 61.3% of surveys; in figures as 'Broken and Incorporated'); and

4. Residual rice straw either cut and removed from the field via baling (e.g., baling; 21.7% of surveys) or left untouched after harvest before flooding (e.g., no action; 1.2% of surveys; in figures as 'Neither').

We categorized the frequency of hunting into the following categories, in order of increasing disturbance:

1. None: there was no hunting on the rice check, elsewhere within the rice field, or elsewhere on the property during the year the check was surveyed;

2. Nearby: hunting occurred elsewhere on the property, but not at the specific rice field that was surveyed;

3. <3 days: hunting occurred within the rice field on average <3 days week $^{-1}$ during the year that was surveyed; and

4. ≥ 3 days: hunting occurred within the rice field on average ≥ 3 days week $^{-1}$ during the year that was surveyed.

For all bird surveys, we never surveyed a rice check during an active hunt day.

We used ArcMap to measure the area and perimeter of each surveyed rice check to examine if bird use was related to the relative shape of the rice check. We calculated a shape index based on the perimeter and area (a smaller index indicates a more square-shaped check and a larger index indicates a more rectangular-shaped check with a greater perimeter relative to area; McGarigal 2014) using the following formula:

$$Shape\ index = \frac{0.25 \times perimeter\ (m)}{\sqrt{area\ (m^2)}} \quad \text{Eq 1}$$

We summarized habitat composition data into three metrics to capture habitat composition likely to affect bird use: (1) the percent of the flooded area within the rice check that contained emergent vegetation, including both rice and other types of vegetation (% water with vegetation), (2) the percent of the flooded area within the rice check with emergent dirt clods, including both vegetated and non-vegetated dirt clods (% dirt clods), and (3) the percent of mudflat present within the rice check, including both vegetated and non-vegetated mud (% mudflat).

Habitat Transect Surveys

After the bird survey and the overall habitat surveys were completed, we conducted more detailed habitat surveys within each rice check. We walked one to three transects perpendicular

https://doi.org/10.15447/sfews.2024v22iss3art3

to the long sides of the rice check, beginning ~50 m from the observation point (Figure 2) and avoiding areas within 50 m of duck-hunting blinds or the end of either side of the field. We walked through the check (parallel to the short side), taking measurements (see below) starting ~1 m from the shore and every 5 m after that, with the last measurement taken ≥ 1 m from the opposite shore. If, after the first transect was completed, we had obtained < 25 measurements, we moved 50 m further into the rice check from the first transect and sampled habitat along a second (and if necessary, a third) transect, until we had ≥ 25 measurements. At each transect sampling point, we measured (1) water depth and (2) average emergent vegetation height above the surface of the water within a 1 m radius. From these measurements, we calculated the mean value and the coefficient of variation for both the water depth and vegetation height (which included zeros when there was no emergent vegetation).

Temporal Variables

In addition to habitat covariates derived from the surveys described above, we also quantified several field-level classification variables that helped describe the temporal nature of the flooded habitat. To account for differences in time of day, we calculated the number of minutes since sunrise that each survey began. To account for date effects, we calculated the number of days since October 1 for each survey. Because post-harvested rice fields were not all flooded at the same time, we also calculated the number of days since flooding had started in each field (hereafter days since flooding started). However, given the length of this study (October to March) and the fact that most fields were flooded in the fall, days since October 1 and the number of days since flooding started in the rice field were strongly correlated (Appendix A Figure A1; Pearson's product moment correlation, $r = 0.83$). Thus, we chose to include the days since flooding started in our analyses, but it is important to note that the interpretation of this variable has implications for both management (time of flood-up) as well as calendar date (days since October 1).

STATISTICAL ANALYSIS

We evaluated bird use of surveyed rice checks using several metrics: (1) abundance of all birds, (2) abundance of four different taxonomic guilds (dabbling ducks, small and medium-sized shorebirds, wading birds, and geese), and (3) species- and family-level diversity. For these analyses, we assumed that there were no differences in detectability among species or taxonomic groups within these predominantly open post-harvest rice fields. We conducted separate analyses, using multimodel inference (see below), in the program R version 4.2.2 (Bates et al. 2015; R Core Team 2022) to evaluate the influence of various habitat and management variables on each metric of bird use. Additionally, we examined where birds were located within rice checks relative to the edges of the rice checks.

Multimodel Inference for Bird Abundance and Diversity Metrics

To identify factors potentially influencing bird use of winter-flooded rice checks, we first identified 14 possible environmental covariates to test (Table 1). We included study year (water year), minutes since sunrise, and the number of days since the rice field started flooding to account for date and timing effects as well as variability among years. Check area (ha) and shape index captured differences in size and shape (typically square to rectangular) among rice checks. Hunting intensity and post-harvest treatment were factors that described the overall human use and management of each rice check. The percent of the flooded area containing dirt clods, the percent of flooded area containing emergent vegetation, the percent of mudflat within the check, and the mean and variation (coefficient of variation: CV) of vegetation height and water depth were continuous variables that characterized the habitat within the rice check. We also included quadratic terms for mean water depth and the number of days since flooding started, after first centering both variables on

Table 1 Candidate variables used in separate analyses of (1) overall bird abundance, (2) abundance of four taxonomic guilds, and (3) bird species richness and diversity metrics within rice checks in the Sacramento Valley, California, during the winters of 2021–2022 and 2022–2023. The spatial scale refers to whether the variable was quantified at the scale of the entire flooded rice check or determined from transect data collected within the rice check.

Model term	Spatial scale	Definition
Study year	Rice check	Whether the survey was conducted during year 1 (2021–2022) or year 2 (2022–2023)
Check area	Rice check	Area of surveyed rice check (hectares)
Days since flood	Rice check	Number of days between the start of flooding at the surveyed rice field and the survey date; included as both linear and quadratic effects
Hunting intensity	Rice check	4 categories; ranked from no hunting on the property to a high intensity (≥ 3 days a week); see text for details
Min since sunrise	Rice check	Number of minutes between sunrise on the survey date and the start time of the survey
% dirt clods	Rice check	Percent of the flooded area of the check in which dirt clods were visible above the surface of the water
% water with veg	Rice check	Percent of the flooded area of the check with emergent vegetation present (includes both rice and other types of vegetation)
% mudflat	Rice check	Percent of the check area composed of mudflat habitat
Post-harvest treatment	Rice check	4 categories based on whether residual rice straw was broken up and/or incorporated into the soil after harvest
Shape index	Rice check	Index based on the ratio of perimeter (m) to area (m^2) of the sampled check; larger values indicate longer, narrower checks
Vegetation height, mean	Transect within check	Mean height of emergent vegetation in the sampled area, averaged across transect measurements (cm)
Vegetation height, variation	Transect within check	Coefficient of variation for mean height of emergent vegetation in the sample area, derived from transect measurements
Water depth, mean	Transect within check	Depth of water within 1 m of sample point, averaged across transect measurements (cm); included as both linear and quadratic effects
Water depth, variation	Transect within check	Coefficient of variation for water depth, derived from transect measurements

their median value; the linear term was required to be included in any model that contained the quadratic term.

We utilized several different types of models and sample distributions for our analyses. We performed separate analyses of bird abundance within rice checks for:

1. All birds;
2. Dabbling ducks (subfamily Anatinae);
3. Small and medium-sized shorebirds (suborder Charadrii, hereafter shorebirds);
4. Wading birds (e.g., herons, egrets, and ibis [order Pelecaniformes], cranes [family Gruidae]); and
5. Geese (subfamily Anserinae).

For these analyses, we used generalized linear models with a second-order negative binomial distribution and a log link (*glmmTMB* function from the R package *glmmTMB*; Brooks et al. 2017), which is most appropriate for analyses of count data when the variance increases non-linearly with the mean. We included the natural log of check area as an offset term in all abundance models to statistically account for the size of the area surveyed, and we included study year in all models. Next, we examined diversity at the species and taxonomic family level using richness (number of species, S), the exponential of the Shannon–Wiener index (species and family level, H'), and the reciprocal of the Simpson's index (species and family level, D; Hill 1973). We used the *diversity* function in the *vegan* package in R (Oksanen et al. 2017) to determine both the Shannon–Wiener and reciprocal Simpson indices, and then we calculated the exponential of the Shannon–Wiener index for analysis. The exponential of the Shannon–Wiener index ($\exp^{H'}$) and the reciprocal Simpson index ($1/D$) can both be interpreted as the effective number of species (MacDonald et al. 2017). To test the variables influencing species richness, we used a generalized linear model with a Poisson distribution and a log link; rice checks that did not have any birds present were included. To test the variables influencing the exponential of the Shannon–Wiener index and the reciprocal Simpson index, we used generalized linear models with a gamma distribution and a log link; rice checks that did not have any birds present were excluded from these analyses. A gamma distribution can be used with non-integer data and ensured that diversity estimates and confidence intervals (CIs) were ≥ 0. For diversity analyses, we included study year and the check area as base variables in all candidate models.

For each analysis, we built a balanced suite of candidate models and compared them using an Akaike Information Criterion (AIC) framework (Burnham and Anderson 2002). Candidate model sets included all combinations of predictor variables up to a maximum of eight total variables, including the base variables, to avoid over-parameterization with our maximum sample size of 253 rice checks (Peterson and Ackerman 2024). Each full candidate set consisted of 3,690 models. After running each set of models, we ranked models according to maximum parsimony using the difference in second-order AIC (ΔAIC_c; Burnham and Anderson 2002) between the best model (lowest AIC_c) and all other models. Models with a $\Delta AIC_c < 2$ from the top model were considered competitive with the top model. We used Akaike model weights (w_i) to represent the relative likelihood of each model given all the models in the candidate set. To evaluate the importance of each variable included in the top model, we calculated evidence ratios by dividing the weight (w_i) of the top model by the weight of the same model without the variable of interest. Additionally, we calculated the adjusted relative importance of each variable, as described in Ackerman et al. (2015), which accounts for the fact that some variables may be present in more models than others because we included some quadratic terms. We also evaluated the direction and magnitude of variable effects using 85% CIs around the conditional model-averaged slope coefficients (Arnold 2010).

To account for uncertainty in model selection, we calculated model-averaged predictions based on models comprising the top 90% of cumulative model weights by multiplying the prediction for each model by its normalized model weight (rescaling the top 90% to 100%) and summing across all included models. We examined variables individually by predicting between the 5th to 95th quantiles of observed values, while holding all other variables constant at either the median value (check area: 8.5 ha; shape index: 1.3; minutes since sunrise: 82.0; percent of water with emergent vegetation: 5.0%; percent of water with dirt clods: 0%; percent mudflat: 0%; mean water depth: 20.5 cm; variation in water depth [CV]: 16.2; mean emergent vegetation height above the water: 1.4 cm; variation in emergent vegetation height [CV]: 245.9) or the most common value for factor levels (post-harvest treatment: residual rice straw broken up and incorporated into the soil; hunting intensity: < 3 days week^{-1}), unless otherwise specified. For the number of days since the start of flooding, we selected 20 days for predictions. For figures, we show back-transformed predicted mean values and 95% CIs for the winter of 2021–2022.

Spatial Distribution of Birds

To evaluate the spatial distribution of different taxonomic groups of birds within the surveyed rice checks, we ran a linear mixed model that compared the distance between bird observations and the nearest shoreline (excluding any interior shorelines created by islands), including six taxonomic groups (dabbling ducks, diving ducks, geese, small shorebirds, medium shorebirds, and wading birds) as a factor, and individual data points weighted by the square root of the number of birds observed at that location. We also included the shape index as a covariate, as well as an interaction between bird taxa and shape index to account for potential differences in the distance to shoreline among taxonomic groups that may vary relative to the shape of rice checks. The rice check was included as a random effect to account for multiple observations within the same rice check. We used the same analysis as taxonomic group, described above, to compare the distance to the shoreline among six species of dabbling ducks (American Wigeon [*Mareca americana*], Gadwall [*M. strepera*], Green-winged Teal [*Anas carolinensis*], Mallard [*A. platyrhynchos*], Northern Pintail, and Northern Shoveler [*Spatula clypeata*]). To account for zeros in this dataset, half of the minimum non-zero distance to the shoreline was added to all data points, and then the distance to the nearest shoreline was natural-log-transformed before analysis. We conducted pairwise, post-hoc comparisons based on model-generated least squares mean distances to shoreline for each taxon, while holding shape index constant at the median value of 1.3.

Additionally, we tested whether increased availability of perch sites increased the number of avian predators present at rice checks, using a generalized linear model with a negative binomial distribution and a log link to compare avian predator counts to the number of perch sites within 50 m of the rice check.

RESULTS

We conducted bird surveys and habitat assessments within 253 rice checks (representing 177 rice fields), for a total area surveyed of 2,158 ha during the fall and winter of 2021–2022 (October 13, 2021 to February 14, 2022) and 2022–2023 (December 8, 2022 to February 6, 2023; Peterson and Ackerman 2024). We counted a total of 143,932 birds, including:

- 124,326 dabbling ducks (86.4%)
- 2,116 other ducks (1.5%; 1,047 diving ducks and 1,069 unidentified ducks)
- 11,480 geese (8.0%)
- 862 small shorebirds (< 1%; includes small sandpipers, Dunlin [*Calidris alpina*], and dowitchers [*Limnodromus* spp.])
- 371 medium shorebirds (< 1%; includes plovers, yellowlegs [*Tringa* spp.], Long-billed Curlew [*Numenius americanus*], Willet [*Tringa semipalmata*], Wilson's Snipe [*Gallinago delicata*], American Avocet [*Recurvirostra americana*], and Black-necked Stilt [*Himantopus mexicanus*])
- 1,056 wading birds (< 1%; includes herons, egrets, White-faced Ibis [*Plegadis chihi*], and Sandhill Crane [*Grus canadensis*])
- 3,721 other birds (2.6%; includes raptors, corvids, gulls, terns, American Coot [*Fulica americana*], and grebes)

These birds comprised 57 different species from 16 families. Individual surveyed rice checks contained 0 to 55,823 birds from 0 to 14 species and up to 7 families. The family Anatidae, including all ducks and geese, comprised 95.8% of all birds observed, and dabbling ducks accounted for 86.4% of all birds. In fact, just three rice checks contained 65.7% of all dabbling ducks observed: 12,040, 14,481, and 55,103, respectively. When birds were observed in a rice check, dabbling ducks comprised a median value of 70.7% of the birds observed. Of the 228 rice checks with birds present, dabbling ducks were observed at 74.6%, wading birds were observed at 34.0%, small and medium shorebirds were observed at 26.3%, geese were observed at 25.0%, and diving ducks were observed at 10.5%. No birds were observed at 9.9% of rice checks (n = 25 checks). Of the birds for which a specific behavior could be identified (excluding birds with behavior recorded as flushed), 72.6% were feeding, 16.0% were roosting, 2.9% were swimming, and 3.1% were flying over the rice check. Only seven birds were observed engaged in breeding behaviors.

Avian predators observed at rice fields included American Kestrel (*Falco sparverius*), Bald Eagle (*Haliaeetus leucocephalus*), Northern Harrier (*Circus hudsonius*), Peregrine Falcon (*Falco peregrinus*),

https://doi.org/10.15447/sfews.2024v22iss3art3

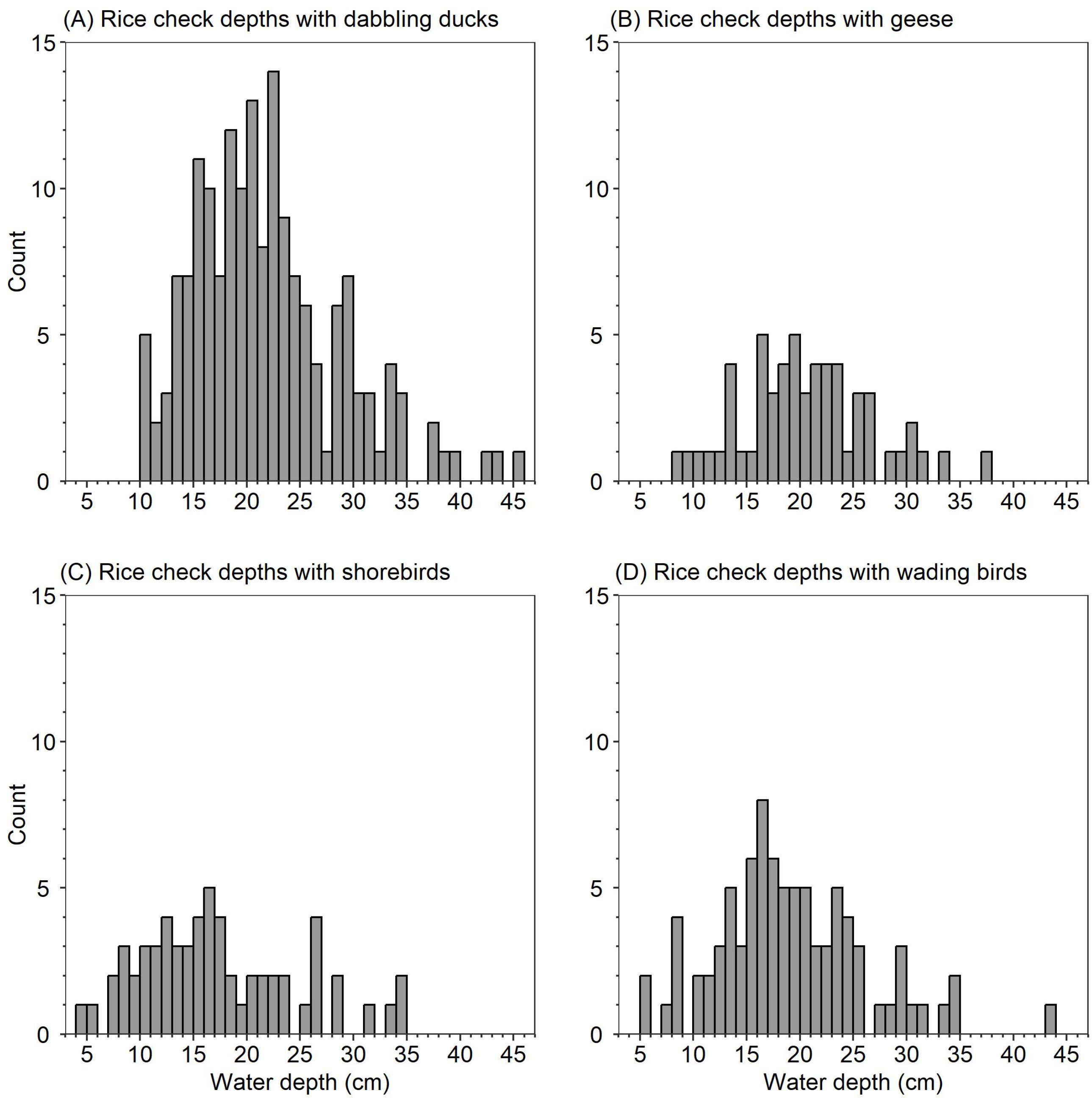

Figure 3 The distribution of mean water depths for rice checks (n = 253 total surveyed rice checks) where (**A**) dabbling ducks, (**B**) geese, (**C**) shorebirds, and (**D**) wading birds were observed during the winters of 2021–2022 and 2022–2023.

Red-shouldered Hawk (*Buteo lineatus*), and Red-tailed Hawk (*B. jamaicensis*), with a maximum of four individual avian predators observed at an individual rice check. The number of avian predators that were observed at rice checks did not increase with the number of perch sites at a rice check (slope = –0.006, z-value = –1.86, p = 0.06).

Rice checks ranged from 0.8 to 26.1 ha (median: 8.5 ha; 5th to 95th quantiles: 2.2 to 16.2 ha), with mean water depths from 4.6 to 45.4 cm (median: 20.5 cm; 9.7 to 34.0 cm; Figure 3). The mean height of emergent vegetation above the surface of the water ranged from 0.0 to 20.8 cm (median: 1.4 cm; 0 to 8.2 cm). Dry substrate was rare (1% of rice checks) and ranged from 10% to 37% of the check when present. The mean percent of each check that was flooded was 98% (median = 100%), and 87% of all checks were fully flooded. Mudflat habitat was observed in 13% of checks, and ranged from 1% to 75% of the check area when present (median: 12% of the check when mud was present). Emergent dirt clods were observed in 13% of checks and comprised 1% to 45% of the flooded area of the rice check when present (median: 5% of the flooded area in checks when clods were present). Rice check shape indices ranged from 0.9 to 2.3 (median: 1.3; 1.0 to 1.7). Rice checks had 0 to 387 perch sites (median: three perch sites).

BIRD ABUNDANCE

All Birds

Birds were observed in 228 of the 253 surveyed rice checks. Overall bird abundance was influenced by water depth and the number of days since the start of flooding, varied with hunting intensity, and decreased with the percent of the rice check with emergent dirt clods (Table 2). The relationship with water depth was non-linear, with the highest overall bird abundance observed at intermediate water depths (approximately 21 cm). The effect of days since the rice check was flooded was also non-linear, with abundance peaking just after the rice fields started flooding (mid-October for most rice fields) and a subsequent decrease in abundance until approximately 83 days after flooding, at which point overall bird abundance began to increase slightly (Figure 4). Overall bird abundance was higher in rice checks where there was no hunting in that rice field nor elsewhere on the property than in rice checks where there was hunting elsewhere on the property or within the rice field at other times during the winter (Figure 4). Study year was a base variable in all candidate model sets but the 85% CI overlapped for the 2 study years, suggesting that overall bird abundance did not differ between years. There were no other competitive models ($\Delta AIC_c \leq 2$ from the top model; Table 2).

Table 2 Model selection results for the abundance of all birds (untransformed count data) within rice fields in the Sacramento Valley, California during the winters of 2021–2022 and 2022–2023. Model selection results for all other taxa are in Appendix A. All models in the full model set (n = 3,690 models) included the base variables of study year and $\log_e$(check area) as an offset as well as all combinations of up to 6 of the remaining variables described in Table 1. Models in this table represent all competitive models with $\Delta AIC_c \leq 2$ from the top model as well as the base model and all models with just one variable removed from the top model (indicated by bold text). The following terms are reported for each model and all subsequent model selection tables: k (number of parameters in the model), −2logL (−2 × log(likelihood)), AIC_c (second order Akaike information criterion), ΔAIC_c (the difference in the AIC_c between the top model and the model of interest), w_i (Akaike model weight), and the evidence ratio (how many times more likely the top model is over the model of interest: obtained by dividing the Akaike model weight of the top model by the Akaike model weight of the model of interest).

Model (base model: study year + offset of $\log_e$(check area))	k	−2LogL	AIC_c	ΔAIC_c	w_i	Evidence ratio
+ days since flood + days since flood^2 + hunting intensity + % dirt clods + water depth + water depth^2	**11**	**2939.47**	**2962.57**	**0.00**	**0.15**	**1.00**
+ days since flood + days since flood^2 + hunting intensity + % dirt clods	**9**	**2946.25**	**2964.99**	**2.43**	**0.05**	**3.36**
+ days since flood + days since flood^2 + hunting intensity + % dirt clods + water depth	**10**	**2945.69**	**2966.60**	**4.03**	**0.02**	**7.51**
+ days since flood + days since flood^2 + hunting intensity + water depth + water depth^2	**10**	**2945.87**	**2966.78**	**4.22**	**0.02**	**8.23**
+ days since flood + hunting intensity + % dirt clods + water depth + water depth^2	**10**	**2960.48**	**2981.39**	**18.83**	**0.00**	**1.22×10^4**
+ hunting intensity + % dirt clods + water depth + water depth^2	**9**	**2965.35**	**2984.09**	**21.52**	**0.00**	**4.72×10^4**
+ days since flood + days since flood^2 + % dirt clods + water depth + water depth^2	**8**	**2969.94**	**2986.53**	**23.96**	**0.00**	**1.60×10^5**
base model: study year + offset of $\log_e$(check area)	3	3015.37	3021.46	58.90	0.00	6.16×10^{12}

https://doi.org/10.15447/sfews.2024v22iss3art3

Using evidence ratios, we estimated that the top model was 1.6×10^5 times more likely than the same model without hunting intensity and 8.2 times more likely than the same model without the percent of the rice check with dirt clods. The top model, containing both linear and quadratic terms for days since the start of flooding, was 4.7×10^4 times more likely than the same model without the linear or the quadratic term for days since flooding. The top model, containing both linear and quadratic terms for water depth, was 3.4 times more likely than the same model without either term for water depth (Table 2). Based on adjusted relative variable importance, the overall bird abundance data most strongly supported an effect of hunting intensity (9.9), followed by the number of days since flooding started (9.6 for the quadratic form), and the percent of the rice check with dirt clods (1.9), with less support for water depth (0.5 for the quadratic form). All other variables had little support, with adjusted relative variable importance values < 0.

Holding other covariates constant, predicted overall bird abundance decreased 92.8% from an average of 1,763.6 birds observed 8 days after the start of flooding (5^{th} quantile), which was approximately late-October for most rice fields, to 126.1 birds observed 83 days after the start of flooding (approximately early January). Bird abundance decreased by 25.7% when the percent of a flooded rice check with dirt clods increased from 0 to 5%; 91.7% of the surveyed rice checks had visible dirt clods in $\leq 5\%$ of the check. Overall bird abundance was 15.6% higher in rice checks with a mean water depth of 21 cm compared to a mean water depth of 10 cm, and overall abundance began to decrease when water depths exceeded 21 cm (Figure 4). Hunting intensity strongly influenced bird abundance, with rice checks where hunting did not occur within the rice field and did not occur elsewhere on the property demonstrating a 1,256.9% to 1,557.2% higher abundance than rice checks where hunting occurred elsewhere on the property ('Nearby') or at varying levels of intensity within the rice field on another day during the winter (Figure 4).

We model-estimated overall bird density for each hectare of flooded rice field, holding all other covariates constant. In a normal year, program participants in the California Winter Rice Habitat Incentive Program are required to hold water for a minimum of 70 days. We extrapolated the estimated densities observed 70 days after flooding, which were the lowest densities observed in the first 70 days, to the total flooded rice field area enrolled in the California Winter Rice Habitat Incentive Program during the 2021–2022 season (16,248 ha) and the 2022–2023 (8,448 ha) season. Using the lowest densities observed between the start of flooding and 70 days after flooding provides a conservative estimate of the minimum potential bird-use-days during the enrollment period. In 2021–2022, the lowest estimated density within the first 70 days of flooding was 16.7 birds ha^{-1}, indicating that the 16,248 ha of enrolled rice fields could provide habitat for 271,312 birds day^{-1} (bird density × enrolled ha of flooded rice fields) for a total of 18,991,840 bird-use-days (bird density × enrolled ha of flooded rice fields × 70 days) in flooded rice fields during the enrollment period (Figure 5). During the 2022–2023 season, the lowest estimated density within the first 70 days of flooding was 17.4 birds ha^{-1}, indicating that the 8,448 ha of enrolled rice fields could provide habitat for 147,315 birds day^{-1} for a total of 10,312,050 bird-use-days during the enrollment period (Figure 5).

Dabbling Ducks

Dabbling ducks were observed in 170 of the 253 surveyed rice checks. Dabbling duck abundance was influenced by water depth and the number of days since flooding started, varied with hunting intensity, and decreased with the shape index, indicating that dabbling duck abundance decreased with an increasing ratio of perimeter-to-check area (Figure 6; Appendix A Table A1). The effect of water depth was non-linear, with the lowest abundance observed at 10 cm water depth, and increasing abundance until the peak at approximately 23 cm, followed by a decrease in abundance until 34 cm. The effect of date was also non-linear, with the highest abundance of dabbling ducks observed shortly after the start of flooding (mid-October for most rice fields)

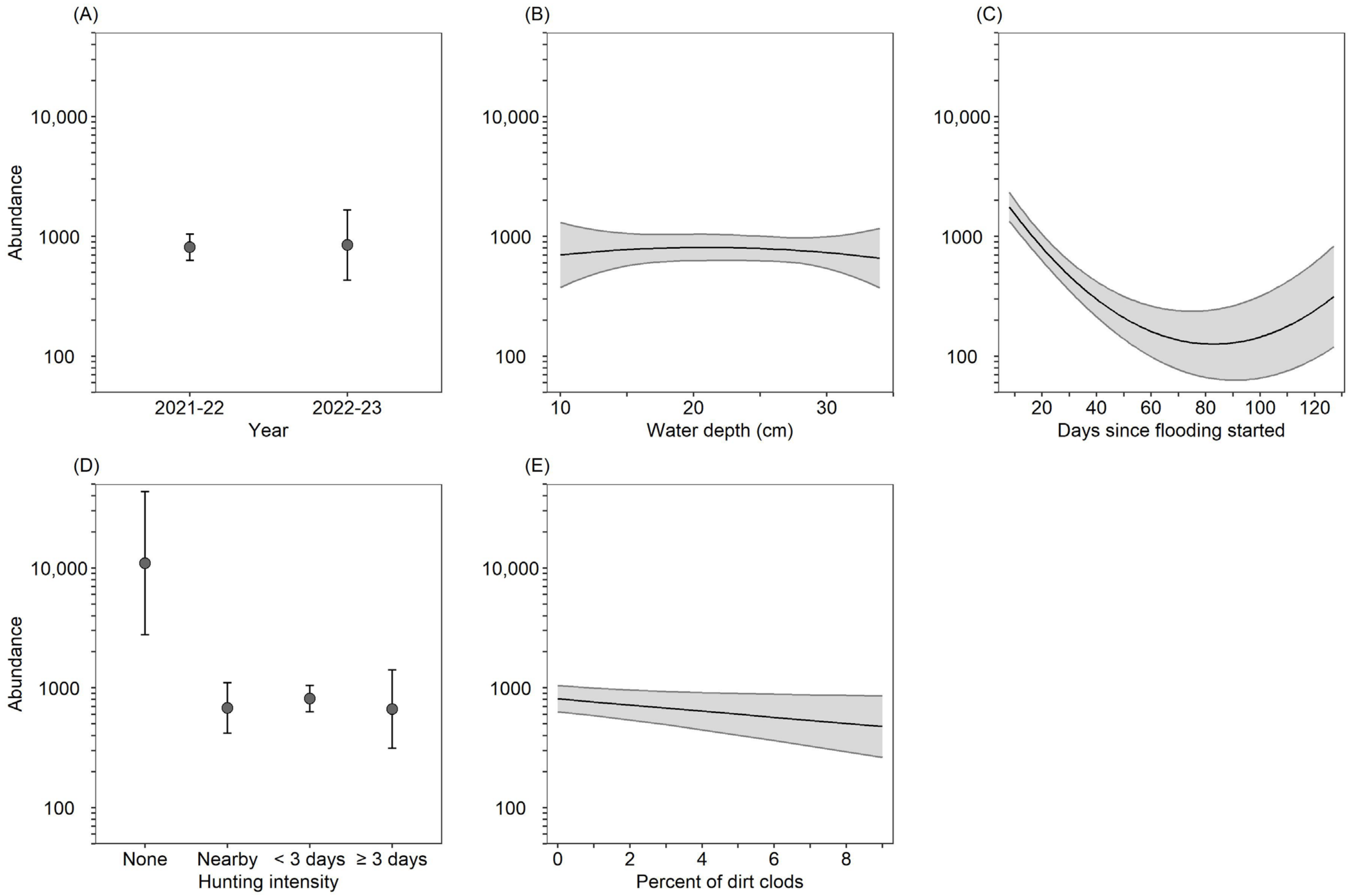

Figure 4 Model-averaged predictions for the abundance of all birds (with 95% confidence intervals) from the 5th to 95th quantile of values observed for each variable within rice checks (n = 253) surveyed in the Sacramento Valley, California, during the winters of 2021–2022 and 2022–2023. Predictions were generated for the winter of 2021–2022 by holding all other variables in the model at their median (check area: 8.5 ha; shape index: 1.3; minutes since sunrise: 82.0; percent water with vegetation: 5%; percent mudflat: 0%; percent of water containing dirt clods: 0%; mean water depth: 20.5 cm; variation in water depth: 16.2; mean vegetation height: 1.4 cm; variation in vegetation height: 245.9) or most common (post-harvest treatment: broken up and then incorporated into the soil [e.g., chiseling or discing]; hunting intensity: < 3 days week^{-1}) values, except for days since flooding started, which was set at 20. For hunting intensity, 'None' means no hunting at that property (n = 7), 'Nearby' means hunting at that property, but not in the rice field containing the surveyed rice check (n = 67), < 3 days means hunting in the rice field that contained the surveyed rice check on average < 3 days week^{-1} (n = 117), ≥ 3 days means hunting occurred in the rice field that contained the surveyed rice check on average ≥ 3 days week^{-1} (n = 62). No rice checks were surveyed on days with active hunting in the rice field.

and a subsequent decrease in abundance until approximately 87 days after flooding, at which point abundance began to slightly increase (Figure 6). Dabbling duck abundance was higher in rice checks where there was no hunting than where there was hunting nearby or hunting within the rice field itself at another time during the winter (Figure 6). Study year was a base variable in all candidate model sets but the 85% CI overlapped for the 2 study years, suggesting that dabbling duck abundance in flooded rice fields did not differ between years. There was one other competitive model, which was identical to the top model except that it excluded the shape index and included the percent of the rice check with dirt clods (Table A1). The model-averaged slope coefficient for the percent of dirt clods was negative, and the 85% CIs did not include zero, suggesting that dabbling duck abundance also

https://doi.org/10.15447/sfews.2024v22iss3art3

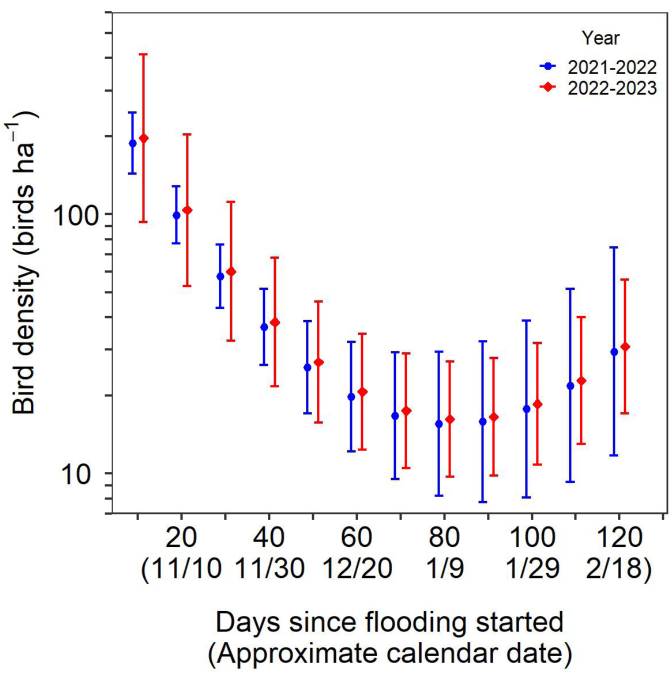

Figure 5 Model-averaged predicted densities (with 95% confidence intervals) in properties that were enrolled in the California Winter Rice Habitat Incentive Program during the winters of 2021–2022 (16,248 ha) and 2022–2023 (8,448 ha) in relation to the number of days since the start of flooding. Although it would have been desirable to examine the date effect within the year as well as the days since the onset of flooding, those metrics were strongly correlated (see Figure A1; Pearson's product moment correlation, $r = 0.83$) and indicated that the average rice field started to be flooded on October 21. The approximate calendar dates are shown below the number of days since the rice field started to be flooded. Predictions were generated by holding all other variables in the model at their median or most common values.

was negatively correlated with the percent of dirt clods in the rice check.

Using evidence ratios, we estimated that the top model was 26.9 times more likely than the same model without hunting intensity and 5.1 times more likely than the same model without shape index. The top model, with the linear and quadratic terms for water depth, was 10.4 times more likely than the same model without either term for water depth. The top model with the linear and quadratic terms for days since flooding started was 16.9 times more likely than the same model without either term for the number of days since flooding started (Table A1). Based on adjusted relative variable importance, the data most strongly supported an effect of water depth (2.5 for the quadratic form), followed by hunting intensity (1.8), the number of days since flooding started (1.8 for the quadratic form), the shape index (1.2), and the percent of dirt clods (1.1). All other variables had little support, with adjusted relative variable importance values < 0.

Holding other covariates at their median values, the predicted abundance of dabbling ducks was 212.3% higher in rice checks with a mean water depth of 23 cm compared to a mean water depth of 10 cm, and then abundance began to decrease again when water depths exceeded 23 cm (Figure 6). Dabbling duck abundance decreased 76.0% from 8 days after the start of flooding (which was approximately mid-October for most rice fields), to approximately 87 days since the start of flooding (which would be approximately mid-January), and then was followed by a slight subsequent increase in dabbling duck abundance (Figure 6). Predicted dabbling duck abundance decreased 64.0% between shape indices of 1.0 and 1.7, as the ratio of perimeter to area increased. As an example, for a rice check of 8.5 ha (85,000 m^2) a shape index of 1.0 would correspond to a square rice check with approximate dimensions of 291.5 m and a perimeter of 1166 m. A shape index of 1.7 would correspond to a rice check that is approximately 896.6 m long and 94.8 m wide with a perimeter of 1983 m.

Shorebirds

Small and medium-sized shorebirds were observed in 60 of the 253 surveyed rice checks. The abundance of shorebirds in rice checks decreased with water depth and shape index, increased with the percent of water that contained emergent vegetation, and was higher in 2022–2023 than during 2021–2022 (Figure 7; Table A2). There were nine other competitive models, all of which included the shape index and the linear term for water depth, and seven of which included the percent of water with emergent vegetation (Table A2). All of the variables that were included in competitive models but not in the top model had 85% CIs around the conditional coefficients that included zero except for the post-harvest treatment. There was some evidence

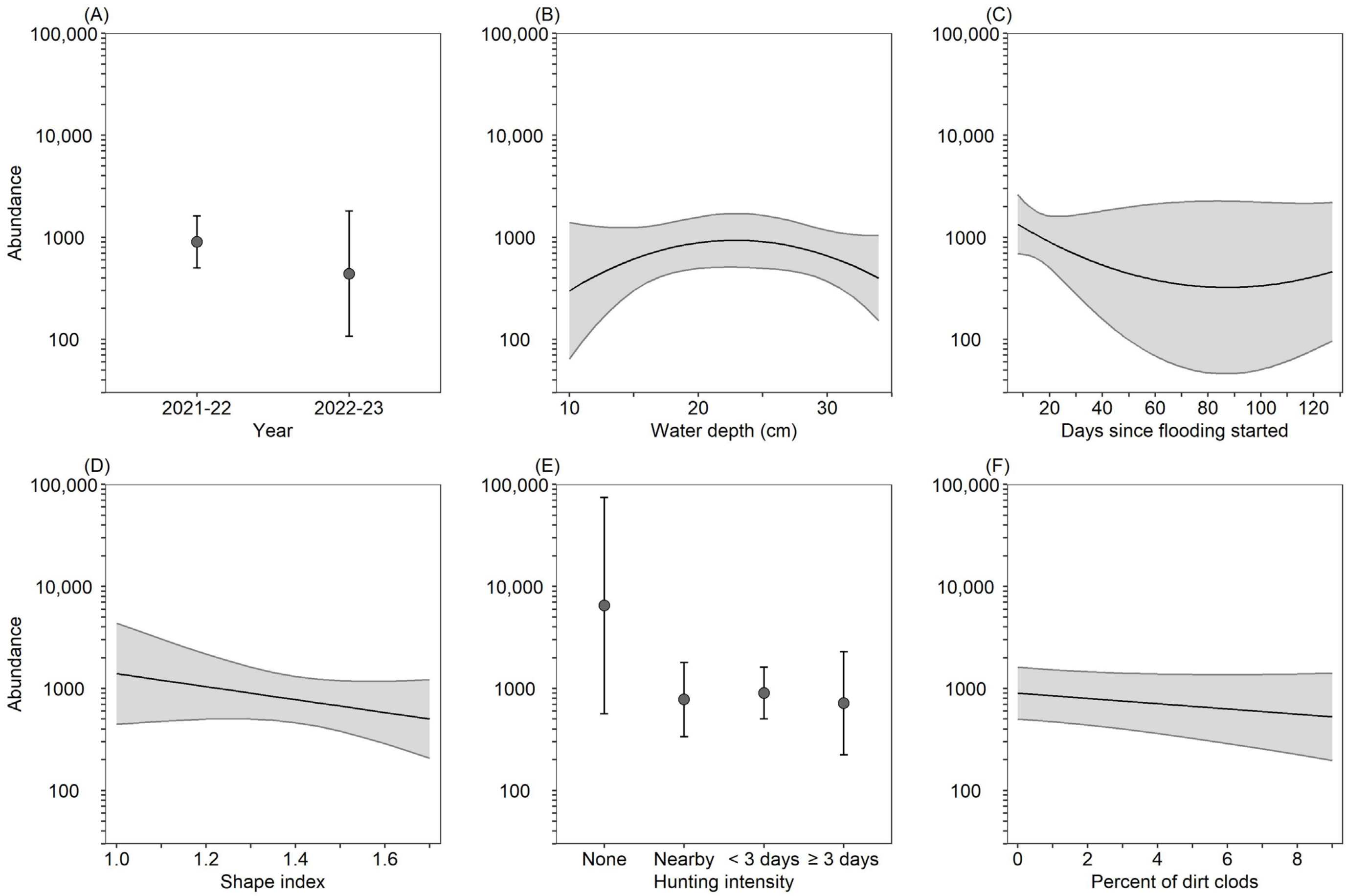

Figure 6 Model-averaged predictions for the abundance of dabbling ducks (with 95% confidence intervals) from the 5th to 95th quantile of values observed for each variable within rice checks (n = 253) surveyed in the Sacramento Valley, California, during the winters of 2021–2022 and 2022–2023. Predictions were generated for the winter of 2021–2022 by holding all other variables in the model at their median or most common values, except for days since flooding started, which was set at 20. For hunting intensity, 'None' means no hunting at that property (n = 7); 'Nearby' means hunting at that property, but not in the rice field containing the surveyed rice check (n = 67); < 3 days means hunting in the rice field that contained the surveyed rice check on average < 3 days week^{-1} (n = 117); ≥ 3 days means hunting occurred in the rice field that contained the surveyed rice check on average ≥ 3 days week^{-1} (n = 62). No rice checks were surveyed on days with active hunting in the rice field.

that shorebird abundance may be lower in rice checks where the residual rice straw was baled and removed, or nothing was done to the rice straw before flooding, compared to rice checks where the residual rice straw was broken up or incorporated into the soil (Figure 7).

Using evidence ratios, the top model with the linear and quadratic terms for water depth was 4.6×10^3 times more likely than the same model without either term for water depth. The top model was 1.6×10^4 times more likely than the same model without the shape index and 3.9 times more likely than the same model without the percent of water with emergent vegetation (Table A2). Based on adjusted relative variable importance, the shorebird abundance data most strongly supported an effect of water depth (8.3 for the linear form and 1.9 for the quadratic form) and the shape index (8.1), with less support for the percent of water containing emergent vegetation (0.5). All other variables had little support, with adjusted relative variable importance values < 0.

Predicted abundance of small and medium-sized shorebirds 20 days after the start of flooding was

https://doi.org/10.15447/sfews.2024v22iss3art3

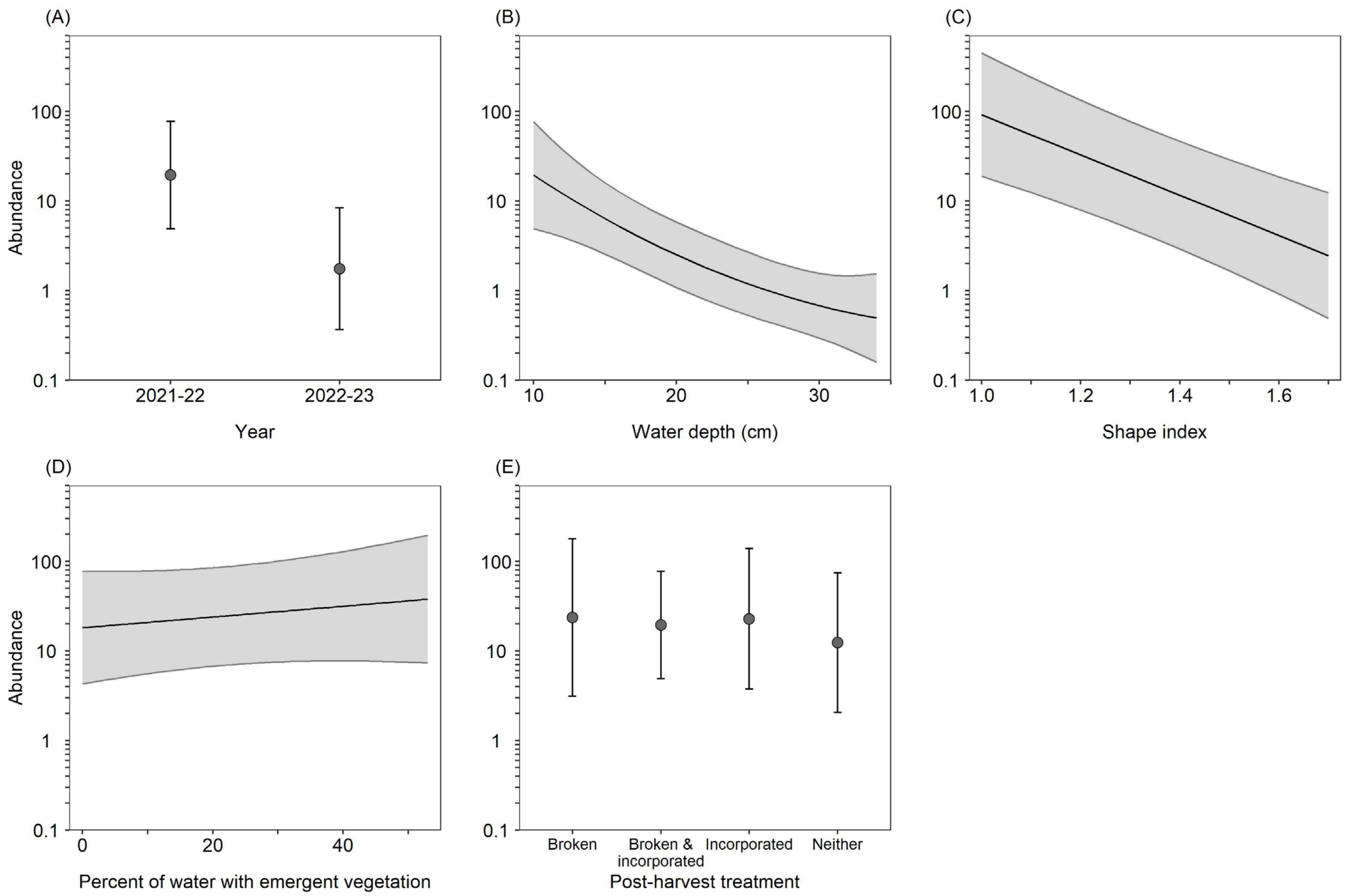

Figure 7 Model-averaged predictions for the abundance of shorebirds (with 95% confidence intervals) from the 5th to 95th quantile of values observed for each variable within rice checks (n = 253) surveyed in the Sacramento Valley, California, during the winters of 2021–2022 and 2022–2023. Shorebird abundances included both small shorebirds (including small sandpipers, Dunlin, and dowitchers) and medium-sized shorebirds (including plovers, yellowlegs, curlews, willets, snipe, avocets, and stilts). Predictions were generated for the winter of 2021–2022 by holding all other variables in the model at their median or most common values, except for days since flooding started, which was set at 20; and water depth, which was set at 10 cm. For post-harvest treatment, 'Broken' means rice straw was mechanically broken up to increase surface area but left in the field (e.g., chopping), 'Broken and Incorporated' means residual rice straw was both broken up and then incorporated into the soil, 'Incorporated' means residual rice straw or stubble was incorporated into the soil (e.g., stomping or rolling), and 'Neither' means residual rice straw was cut and removed from the field via baling or left untouched after harvest before flooding.

91.0% lower in the winter of 2022–2023 than in the winter of 2021–2022, holding water depth at 10 cm and all other covariates at their median values (Figure 7). We observed a 49.9% decrease in shorebird abundance as water depths increased from 10 to 13 cm. For the winter of 2021–2022, shorebird abundance decreased by 91.9%, from an average of 19.4 birds to 1.6 birds in a rice check, as water depths increased from 10 to 23 cm (Figure 7). Additionally, the abundance of shorebirds at 10-cm water depths decreased 97.3% between shape indices of 1.0 and 1.7.

Wading Birds and Geese

Results for factors that influenced the abundance of wading birds and geese are provided in Appendix B.

SPECIES AND FAMILY LEVEL DIVERSITY

Species Richness

The absolute number of observed species (n = 252 rice checks; excluding one rice check where shorebirds could not be identified to species) increased with check area, variation in vegetation height, and percent of mudflat, and was 86.7% higher in the winter of 2021–2022 (5.3 species in a rice check) than the winter of 2022–2023 (2.9 species in a rice check; Figure A4; Table A5). The effect of days since flooding started was non-linear, with a small initial decrease in species richness followed by an increase after the check had been flooded for approximately 68 days (Figure A4). Hunting intensity was also included in the top model, with the lowest species richness predicted for the rice checks with the highest intensity of hunting (≥ 3 days week^{-1}), and the highest species richness observed in the rice checks where there was either no hunting on the property or hunting only occurred nearby but not within the rice field (Figure A4). Fifteen other models were competitive with the top model and contained all of the same variables as the top model, except for the percent of mudflat in the rice check (Table A5). Although some competitive models did not include the percent of mudflat in the rice check, the 85% CI around the conditional slope coefficient did not include zero. There was some biological support for a negative relationship between species richness and the shape index, because the 85% confidence interval around the conditional slope coefficient did not include zero, suggesting that more species may have used square-shaped rice checks where there was a smaller ratio of perimeter to area. The CIs around the conditional slope coefficients for all other variables in competitive models that were not in the top model included zero, suggesting those additional variables were not important.

Using evidence ratios, we estimated that the top model was 2.2×10^3 times more likely than the same model without hunting intensity, 272.2 times more likely than the same model without variation in vegetation height, and 1.5 times more likely than the same model without the percent of mudflat in the rice check. The top model with the linear and quadratic term for days since flooding started was 3.2 times more likely than the same model without either term for days since flooding started (Table A5). Based on adjusted relative variable importance, the data most strongly supported an effect of hunting intensity (5.6), and variation in vegetation height (4.6), followed by weaker support for the number of days since flooding started (1.4 for the quadratic form) and the percent of mudflat (< 0.1). All other variables had little support, with adjusted relative variable importance values < 0.

Holding other covariates at their median values and 20 days after the rice check started flooding, the predicted mean number of species using rice checks in the winter of 2021–2022 increased from 4.2 species in a 2-ha check to 7.0 in a 16-ha check (Figure A4). Species richness was 37.9% lower in rice checks within fields that were being hunted at high intensity (≥ 3 days week^{-1}) and 14.2% lower in rice checks within fields that were being hunted at a lower intensity (< 3 days week^{-1}) in comparison with rice checks where hunting occurred elsewhere on the property but not within the surveyed rice field. Furthermore, between 8 and 68 days after the start of flooding, the mean number of species decreased 11.7% during both the winters of 2021–2022 and 2022–2023, and then species richness began to increase again (Figure A4).

Species Diversity

The top model using the reciprocal Simpson's index (1/D; Table 3; n = 227 rice checks; excludes checks with zero birds and the rice check where shorebird species could not be identified) increased with check area, variation in vegetation height, and the percent of mudflat in the rice check and decreased with the number of minutes since sunrise. The effective number of species was 50.3% higher in the winter of 2021–2022 than in the winter of 2022–2023 (Figure 8). There was also a non-linear effect of water depth, with species diversity decreasing from a water depth of 10 cm to approximately 19 cm, and then increasing from 19 cm to 34 cm (Figure 8). Hunting intensity also was included in the top model, with the lowest species diversity observed in rice checks within fields where hunting

Table 3 Model selection results for species level diversity, as (**A**) the reciprocal of Simpson's index: $1/D$ and (**B, continued on next page**) the exponential of the Shannon-Wiener index: $\exp(H')$ within rice fields in the Sacramento Valley, California during the winters of 2021–2022 and 2022–2023. All models in the full model set (n = 3,690 models) included the base variables of study year and check area as well as all combinations of up to 6 of the remaining variables described in Table 1. Models in this table represent all competitive models with $\Delta AIC_c \leq 2$ from the top model as well as the base model and all models with just one variable removed from the top model (indicated by bold text).

Model (base model: study year + check area)	k	−2LogL	AIC_c	ΔAIC_c	w_i	Evidence ratio
A. Reciprocal of Simpson's index: $1/D$						
+ variation in veg height + hunting intensity + water depth + water depth^2 + min since sunrise + % mud	**12**	**503.47**	**528.93**	**0.00**	**0.06**	**1.00**
+ variation in veg height + hunting intensity + water depth + water depth^2 + min since sunrise	**11**	**505.91**	**529.13**	**0.20**	**0.05**	**1.11**
+ variation in veg height + hunting intensity + water depth + water depth^2 + min since sunrise + veg height	12	504.53	529.98	1.05	0.04	1.69
+ variation in veg height + hunting intensity + water depth + water depth^2 + min since sunrise + % dirt clods	12	504.54	530.00	1.07	0.03	1.71
+ variation in veg height + hunting intensity + water depth + water depth^2 + min since sunrise + % water with veg	12	504.71	530.16	1.24	0.03	1.85
+ variation in veg height + hunting intensity + water depth + water depth^2 + min since sunrise + days since flood	12	504.75	530.21	1.28	0.03	1.90
+ variation in veg height + hunting intensity + water depth + water depth^2 + % mud	**11**	**507.41**	**530.64**	**1.71**	**0.03**	**2.35**
+ variation in veg height + hunting intensity + water depth + water depth^2 + min since sunrise + shape index	12	505.21	530.67	1.74	0.03	2.39
+ variation in veg height + hunting intensity + water depth + water depth^2 + min since sunrise + variation in water depth	12	505.42	530.88	1.95	0.02	2.66
+ variation in veg height + hunting intensity + water depth + min since sunrise + % mud	**11**	**508.57**	**531.80**	**2.87**	**0.01**	**4.19**
+ variation in veg height + hunting intensity + min since sunrise + % mud	**10**	**513.14**	**534.16**	**5.23**	**0.00**	**13.64**
+ variation in veg height + water depth + water depth^2 + min since sunrise + % mud	**9**	**515.75**	**534.58**	**5.65**	**0.00**	**16.84**
+ hunting intensity + water depth + water depth^2 + min since sunrise + % mud	**11**	**512.38**	**535.60**	**6.67**	**0.00**	**28.13**
base model: study year + check area	4	539.87	548.05	19.12	0.00	1.42×10^4

occurred and the highest species diversity observed in the rice checks where hunting (a) only occurred on the property but not within the surveyed rice fields or (b) did not occur at all in either the field or elsewhere on the property (Figure 8). For the reciprocal Simpson's index, there were eight competitive models, all of which included the variation in vegetation height, hunting intensity, and the linear and quadratic terms for water depth, but not all of which contained the percent of mudflat in the check and the number of minutes since sunrise (Table 3). All of the variables that were in a competitive model and not in the top model had 85% CIs around the conditional slope coefficient that included zero.

The top model for the exponentiated Shannon–Wiener index ($\exp^{H'}$; Table 3) was the same as the reciprocal Simpson's index, except that the top model excluded the number of minutes since sunrise.

Using evidence ratios, we estimated that the top model for the reciprocal Simpson's index was 28.1 times more likely than the same model without variation in vegetation height, 16.8 times more likely than the same model without hunting intensity, 13.6 times more likely than the same model without the quadratic and linear terms for water depth, 2.4 times more likely than the same model without the number of minutes since

Table 3 *continued*

Model (base model: study year + check area)	k	−2LogL	AIC_c	ΔAIC_c	w_i	Evidence ratio
B. Exponential of the Shannon–Wiener index: exp(*H′*)						
+ variation in veg height + hunting intensity + water depth + water depth^2 + % mud	**11**	**588.45**	**611.68**	**0.00**	**0.04**	**1.00**
+ variation in veg height + hunting intensity + water depth + water depth^2 + % mud + min since sunrise	12	586.67	612.12	0.45	0.03	1.25
+ variation in veg height + hunting intensity + water depth + water depth^2 + % mud + % dirt clods	12	586.84	612.30	0.62	0.03	1.36
+ variation in veg height + hunting intensity + water depth + water depth^2 + % mud + % water with veg	12	586.99	612.45	0.77	0.03	1.47
+ variation in veg height + hunting intensity + water depth + % mud + % water with veg	11	589.48	612.71	1.03	0.03	1.68
+ variation in veg height + hunting intensity + water depth + water depth^2 + % mud + shape index	12	587.49	612.95	1.27	0.02	1.89
+ variation in veg height + hunting intensity + water depth + water depth^2 + % mud + days since flood	12	587.69	613.15	1.47	0.02	2.08
+ variation in veg height + hunting intensity + water depth + water depth^2 + % mud + veg height	12	587.79	613.25	1.57	0.02	2.19
+ variation in veg height + hunting intensity + water depth + water depth^2 + min since sunrise	11	590.16	613.38	1.71	0.02	2.35
+ variation in veg height + hunting intensity + water depth + % mud	**10**	**592.39**	**613.41**	**1.73**	**0.02**	**2.37**
+ variation in veg height + hunting intensity + water depth + % mud + min since sunrise + % water with veg	12	588.13	613.58	1.91	0.02	2.59
+ variation in veg height + hunting intensity + water depth + water depth^2 + min since sunrise + % dirt clods	12	588.19	613.65	1.97	0.02	2.68
+ variation in veg height + hunting intensity + water depth + water depth^2	**10**	**592.79**	**613.81**	**2.13**	**0.01**	**2.90**
+ variation in veg height + hunting intensity + % mud	**9**	**596.84**	**615.67**	**3.99**	**0.01**	**7.35**
+ hunting intensity + water depth + water depth^2 + % mud	**10**	**598.00**	**619.02**	**7.34**	**0.00**	**39.26**
+ variation in veg height + water depth + water depth^2 + % mud	**8**	**601.75**	**618.41**	**6.74**	**0.00**	**29.02**
base model: study year + check area	4	621.34	629.52	17.84	0.00	7.48×10^3

sunrise, and only 1.1 times more likely than the model without the percent of mudflat (Table 3). Based on adjusted relative variable importance, the species diversity data most strongly supported an effect of variation in vegetation height (2.9), followed by water depth (2.4 for the quadratic form), and hunting intensity (2.4), followed by weaker support for the number of minutes since sunrise (0.8) and the percent of mudflat (0.4). All other variables had little support, with adjusted relative variable importance values < 0.

Family Diversity

Results for factors influencing family diversity are provided in Appendix B.

MICROHABITAT USE AND SPATIAL DISTRIBUTION OF BIRDS

Overall, 77.9% of observed birds were in rice checks with mean water depths of 15 to 25 cm (Figure 9), and 91.8% of those birds were dabbling ducks. Of birds with an assigned microhabitat (n = 141,775 birds), 99.0% were observed in the water within rice checks. Internal or external check levees, structures, and perch sites accounted for 0.6% of bird observations, mudflat accounted for 0.3%, and < 0.1% were in dry microhabitats. Of bird observations within the water, 76.5% were in non-vegetated areas, 23.3% were in areas with emergent rice stubble, and 0.2% were in other vegetation.

https://doi.org/10.15447/sfews.2024v22iss3art3

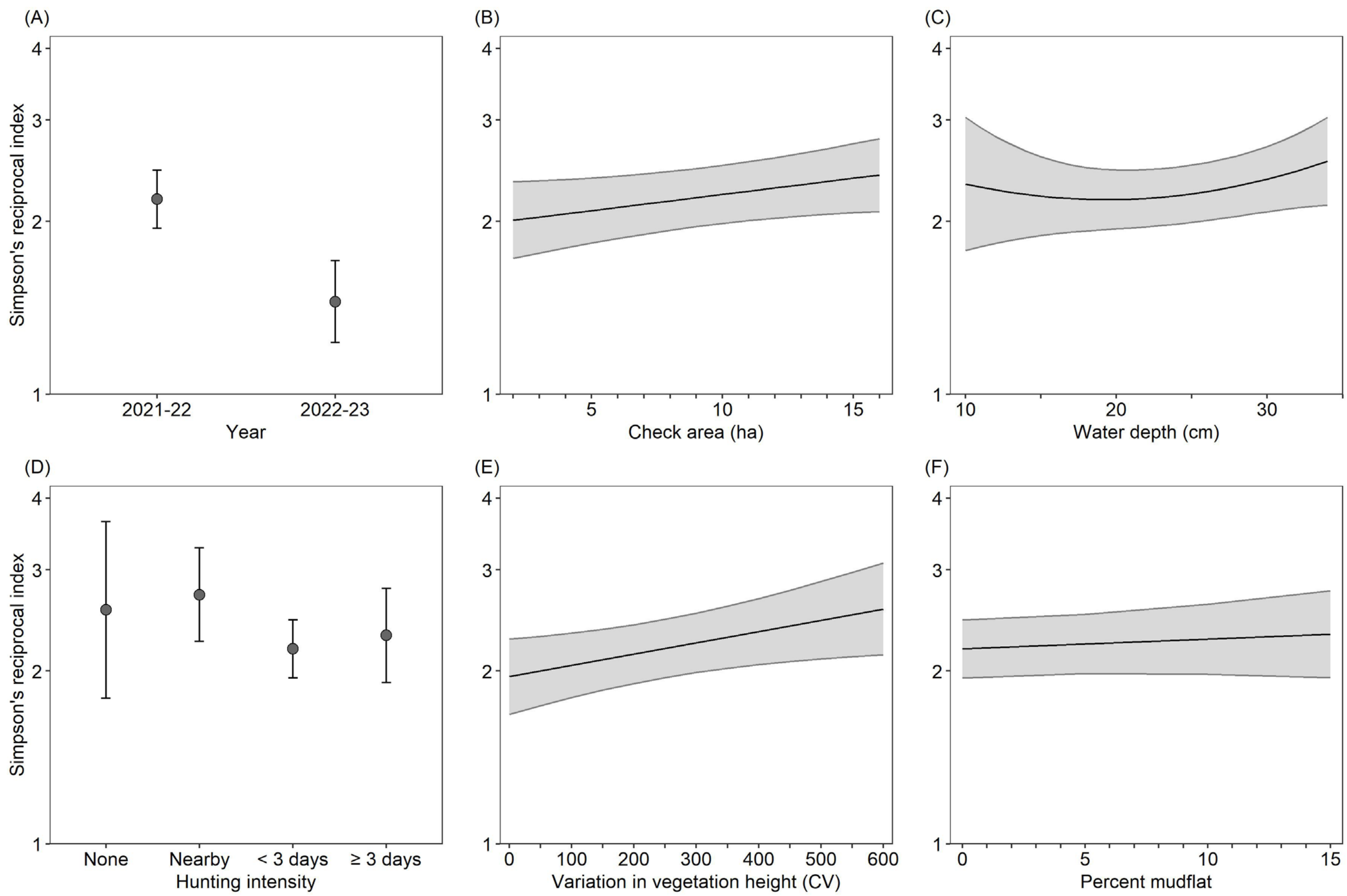

Figure 8 Model-averaged predictions for species diversity (with 95% confidence intervals), calculated using the reciprocal Simpson's index (1/D; n = 227 rice checks), which can be interpreted as the effective number of species, from the 5th to 95th quantile of values observed for each variable within rice checks surveyed in the Sacramento Valley, California. Predictions were generated for the winter of 2021–2022 by holding all other variables in the model at their median or most common values, except for days since flooding started, which was set at 20. For hunting intensity, 'None' means no hunting at that property (n = 7); 'Nearby' means hunting at that property, but not in the rice field containing the surveyed rice check (n = 61); 'Low' means hunting at the surveyed rice check on average < 3 days week^{-1} (n = 106); 'High' means hunting at the surveyed rice check on average ≥ 3 days week^{-1} (n = 53). No rice checks were surveyed on days with active hunting in the rice field.

We found a significant interactive effect between taxon and shape index on the distance ($\log_e$–transformed) between bird observations and the nearest shoreline (X^2_5 = 11.9, p = 0.037). Pairwise comparisons, holding shape index at the median value of 1.3, showed that wading birds were observed closest to shorelines (9.3 m), followed by medium shorebirds (15.1 m), geese (20.0 m), small shorebirds (22.4 m), dabbling ducks (35.9 m), and diving ducks (55.9 m; Figure 10A). Dabbling duck species varied in their distance to shoreline, and the distance to shoreline by species was affected by an interaction between species and shape index (X^2_5 = 45.2, p > 0.001). Pairwise comparisons, holding shape index at the median value of 1.3, showed that American Wigeon, Green-winged Teal, Mallard, and Northern Shoveler were located closest to the shoreline (back-transformed least squares mean distance to shore of 30.4 to 33.7 m), with Northern Pintail located slightly farther from shore (40.1 m), and Gadwall observed the farthest from shore (70.7 m; Figure 10B).

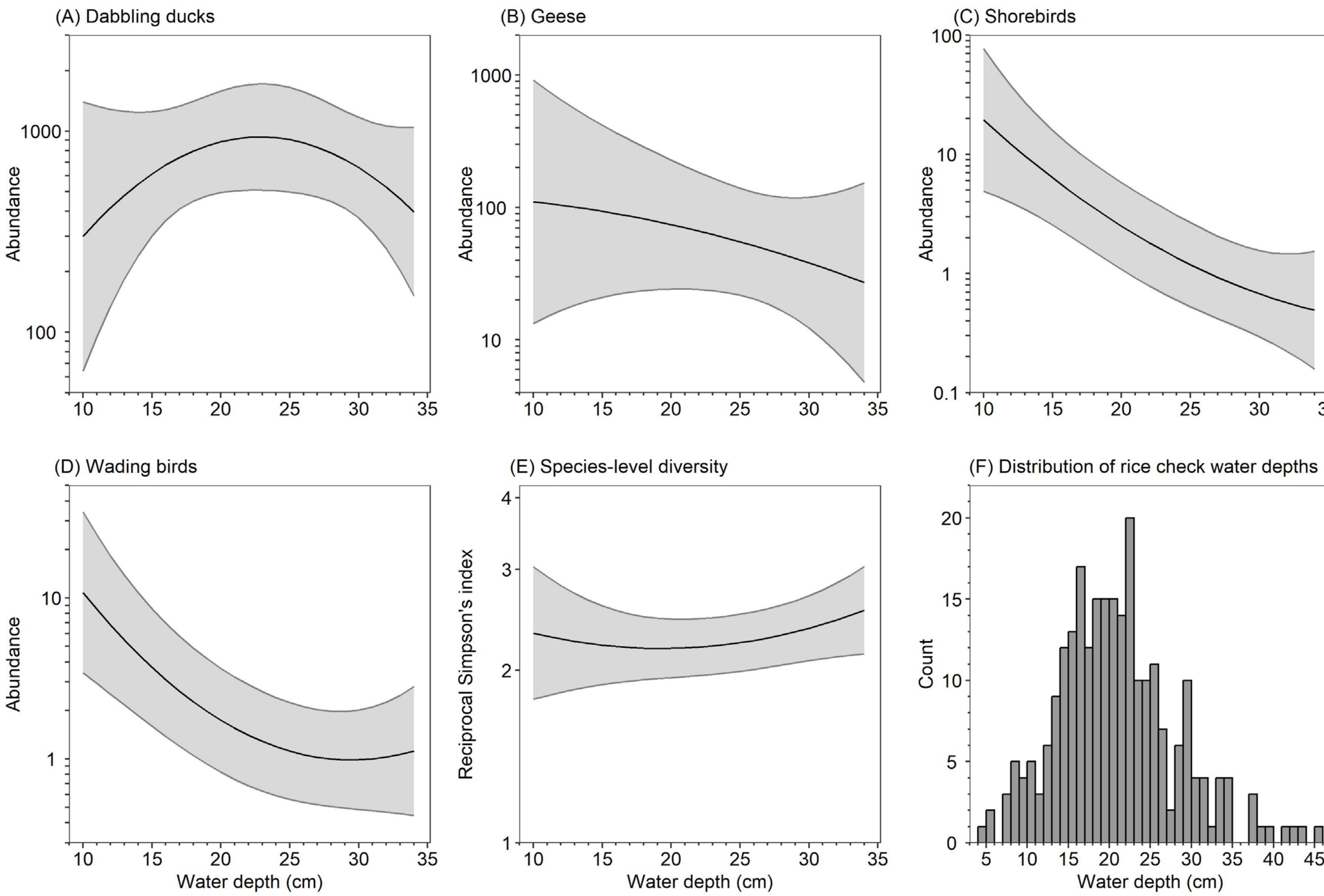

Figure 9 Model-averaged predictions (with 95% confidence intervals) for the abundance of (**A**) dabbling ducks, (**B**) geese, (**C**) small and medium shorebirds, (**D**) wading birds, and (**E**) species level diversity (reciprocal Simpson's index) correlated with the water depth of winter-flooded rice fields in the Sacramento Valley, California. The range of depths for panels **A** through **E** includes the 5th to 95th quantile of observed water depths for all surveyed rice checks. Predictions were generated for the winter of 2021–2022 by holding all other variables in the model at their median or most common values, except for days since flooding started, which was set at 20 days. Panel (**F**) shows the distribution of the mean water depths observed within all 253 rice checks that were surveyed during the winters of 2021–2022 and 2022–2023.

DISCUSSION

Due to substantial losses of natural wetlands, winter-flooded rice fields have become increasingly important habitat for migrating and overwintering waterfowl within California's Central Valley (Gilmer et al. 1982; Heitmeyer et al. 1989; Elphick and Oring 1998; Fleskes et al. 2005; Ackerman et al. 2006). The California Department of Fish and Wildlife's California Winter Rice Habitat Incentive Program was established to incentivize the flooding of rice fields after harvest to provide more wetland habitat for waterbirds during the fall and winter. We conducted bird surveys in 253 rice checks totaling 2,158 ha of winter-flooded rice habitat (9% of the area of winter-flooded rice fields enrolled in the program for those 2 years) to evaluate habitat attributes and management actions that influenced bird abundance and diversity within these winter-flooded rice fields enrolled in the program. We counted 143,932 birds from 57 species, 86% of which were dabbling ducks, 8% were geese, and 1% were shorebirds. We identified several habitat variables that could be managed or prioritized by landowner incentive programs to increase bird use of winter-flooded rice, including the depth of water, size and shape of rice checks, variability in the emergent vegetation height, availability of

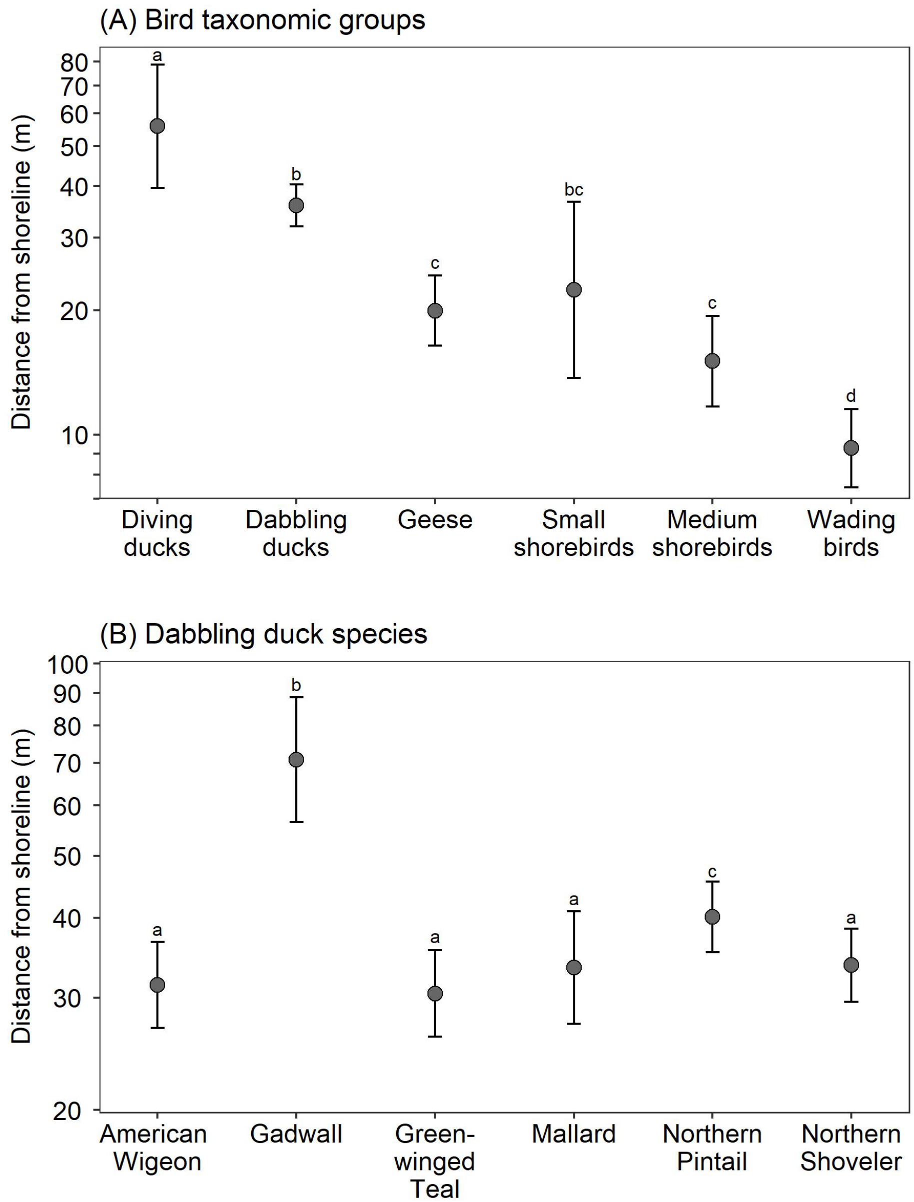

Figure 10 Model-predicted least squares mean distances (with 95% CI) between observed locations and the nearest shoreline within rice checks for (**A**) bird taxonomic groups and (**B**) dabbling duck species. Winter-flooded rice fields (n = 253 rice checks) were surveyed in the Sacramento Valley, California, during the winters of 2021–2022 and 2022–2023. Letters denote groups that were significantly different ($p > 0.05$), based on pairwise post-hoc tests, predicted for a shape index of 1.3 (median shape index).

mudflat habitat within rice fields, total number of days the rice field had been flooded, intensity of hunting, and post-harvest treatment of residual rice straw.

Overall, the greatest number of birds occurred after 8 days of flooding and when rice fields were flooded to a water depth of 21 cm and had no emergent dirt clods or nearby hunting. The greatest number of dabbling ducks were also observed after 8 days of flooding and when rice fields were flooded to a water depth of 23 cm, were more square- than rectangular-shaped, and had no hunting nearby. We observed the greatest number of shorebirds in rice fields that were flooded to a water depth of 10 cm, that were more square-shaped, and had emergent vegetation present in 53% of the flooded area. The greatest number of wading birds were also observed after 8 days of flooding and when rice fields were flooded to a water depth of 10 cm, with no emergent dirt clods, and when residual rice straw was incorporated into the soil after harvest. The greatest number of geese occurred after 8 days of flooding and in rice fields with the greatest variation in water depth and no emergent vegetation. The greatest species diversity was observed at the shallowest (10 cm) and deepest (34 cm) water depths, and when rice checks had large variation in vegetation height and no hunting in the surveyed rice field.

Water Depth

Water depth was consistently one of the most influential habitat characteristics of rice checks on bird abundance and diversity. In the present study, we found strong support for quadratic effects of mean water depth on the abundance of dabbling ducks, shorebirds, and wading birds (Figure 9). Shorebird and wading bird abundances were higher within rice checks at shallower depths (4.6 to 13 cm; shallowest surveyed rice check was 4.6 cm) and declined continuously with increasing depth. In contrast, the greatest abundance of dabbling ducks occurred within rice checks at intermediate water depths around 23 cm (Figure 9). Rice checks with the highest diversity were those with shallower water depths (< 13 cm), and the lowest diversity was observed in rice checks with intermediate water depths (19 to 26 cm). Previous studies have shown that shorebirds and wading birds preferred shallower water (3 to 13 cm), diving species (e.g., diving ducks, grebes) preferred deeper water (24 to 33 cm), and the greatest number of species occurred at 15 to 20 cm (Fasola and Ruiz 1996; Elphick and Oring 1998; Dybala et al. 2017). Strum et al. (2013) also found strong support for a quadratic effect of water depth in rice fields, with the most attractive depths varying among taxa. Because many shorebirds migrate through the Central Valley in the early fall, maintaining some rice fields at shallow water depths (≤ 13 cm) could increase habitat availability for migrating shorebirds during this critical time (Shuford et al. 2019). Furthermore, in midwinter, maintaining rice fields at a variety of water depths between 10 and 23 cm would be likely to support a greater diversity of waterbird species within rice fields (Figure 9). Late in the winter, intentionally staggering the timing of drawdown could provide a variety of available water depths and prolong habitat availability, particularly for shorebirds (Sesser et al. 2018).

Days Since Flooding

Overall bird abundance; abundance of dabbling ducks, geese, and wading birds; and species richness were related to the number of days since the rice field started to be flooded. After accounting for other covariates, this U-shaped relationship indicated that overall bird abundance, dabbling duck abundance, and the total number of species were all greatest shortly after the start of flooding (mid-October), decreased until approximately 70 to 83 days after the start of flooding, and then increased slightly through January and February. For the median-sized rice check (8.5 ha), model-estimated total bird abundances in the present study were 1,763 (2021–2022) and 1,841 birds (2022–2023) after 8 days of flooding (late October), and then dropped to a low of 126 and 132 birds after 83 days of flooding (early January), before increasing to 315 and 329 birds after 127 days of flooding (late February). Similarly, densities were 216 birds ha^{-1} (2021–2022) and 225 birds ha^{-1} (2022–2023) at 8 days after the start of flooding and 16 birds ha^{-1} after 83 days of flooding. The densities we observed were considerably higher during the fall period and more similar in late winter compared to other rice studies (0 to 38 birds ha^{-1}; Bird et al. 2000; Elphick and Oring 2003; Strum et al. 2013; Sesser et al. 2016).

This U-shaped effect of bird abundance and density in relation to the number of days since the start of flooding was likely related to a combination of changes in the availability of other wetland habitats in the Central Valley, temporal changes in food availability within flooded rice fields, and the timing of bird migration into California. Although the timing of flood-up is variable among rice fields, many winter-flooded rice fields begin to hold water in October, before the waterfowl hunting season—thus, creating habitat at a time in the Central Valley when there is less seasonal and temporary wetland habitat available (Donnelly et al. 2022). Higher bird densities upon initial flooding might also result from birds, especially dabbling ducks

https://doi.org/10.15447/sfews.2024v22iss3art3

(86% of surveyed birds), rapidly responding to the availability of waste rice seed accessed through their preferred foraging strategy of dabbling in water. The high early-season bird densities in flooded rice fields highlight the importance of early-season flooding through the California Winter Rice Habitat Incentive Program to provide habitat when fewer alternative wetland habitats are available. As more rice fields are flooded and wetland habitat availability increases through the winter (Donnelly et al. 2022), birds may spread out on the landscape and bird densities in flooded rice habitat may decrease (Figure 5). The decline in bird use after initial flooding may also be due in part to depletion of rice seeds over time via consumption and decomposition (Naylor 2002; Manley et al. 2004; Greer et al. 2009; Lourenço et al. 2010). Consequently, there could be diminishing returns in the value of flooded rice fields for bird habitat when water is held for long periods of time. However, invertebrates are an important component of waterfowl diet in the late winter and early spring when protein is required for egg formation (Krapu 1979; Swanson et al. 1985; Miller 1987; Tidwell et al. 2013), and rice fields that hold water for longer periods of time provide an opportunity for invertebrate populations to increase in late winter (Manley et al. 2004). At the same time, bird abundance and species composition change throughout the fall and winter according to the timing of migration and additional ecological factors, including the timing and quantity of winter rainfall. Once birds are in central California, increased winter rainfall can cause waterbirds to move inland from coastal habitats to flooded habitats in the Central Valley, including rice fields, whereas greater numbers of waterbirds may be observed on the coast during drier years (Warnock et al. 1995; Stenzel and Page 2018). The increased total bird abundance we observed after more than 100 days of flooding (approximately early February) may reflect the beginning of spring migration and suggests that rice fields that remain flooded through late winter are important to meet the habitat needs of wintering waterbirds in the Central Valley (Sesser et al. 2018).

Rice Check Habitat

Several other habitat variables—including the shape of rice checks, variation in emergent vegetation height, the percent of mudflat within rice checks, and the percent of dirt clods within rice checks—were important predictors of abundance for different taxonomic groups of birds, species richness, and diversity within rice checks. Dabbling duck and shorebird abundances decreased as rice checks got longer and narrower (more rectangular in shape with an increasing perimeter-to-area ratio; Figures 6 and 7), suggesting that more square-shaped rice checks had greater use by dabbling ducks and shorebirds. Species richness, species diversity, and family diversity were all positively related to the variation in vegetation height within rice checks. At the species level, variation in vegetation height was the habitat variable that had the greatest influence on diversity, suggesting that having variation in the height of emergent vegetation within or among rice checks may be an important management action that could result in a greater number of species using flooded rice fields. The percent of mudflat habitat within the rice check had a positive effect on diversity at both the species level and family level, despite less than 1% of birds being observed in mudflat habitat. Our data suggest that having some mudflat habitat within flooded rice checks and providing a range of emergent vegetation heights may increase the diversity of birds using flooded rice fields. Microhabitat diversity could be achieved by leaving some areas of taller rice stubble while mowing other areas shorter to provide a variety of vegetation heights and coverage, discing (or otherwise plowing) fields in strips rather than uniformly, and flooding some rice checks—or rice fields—more shallowly to leave more exposed mudflat habitat for shorebirds. However, implementing these practices could affect maintenance costs and effort for landowners, which could warrant further research and consideration by incentive programs of potential added costs.

Post-Harvest Rice Management

There was some indication that habitat management related to the post-harvest treatment of residual rice straw influenced bird use of flooded rice fields. The overall bird use of flooded rice fields—as well as dabbling duck and wading bird abundances—were all negatively correlated with the percent of emergent dirt clods within the flooded area. It is possible that post-harvest treatments (e.g., discing) that produce large dirt clods in the process of breaking up and incorporating residual rice into the soil reduced the accessibility of food for some birds by turning and burying seeds and waste rice under the soil (Garr 2014; Matthews 2019). Moreover, higher wading bird abundance was observed in rice fields where residual rice straw was incorporated into the soil substrate (e.g., stomping or rolling; 12% of surveys) than in rice fields where the residual rice straw was broken up and left on top of the soil (e.g., chopping; 4% of surveys) or broken up first and then incorporated into the soil (e.g., chiseling or discing; 61% of surveys). In the present study, there was some indication that shorebird abundance was lowest in the 23% of rice checks where the rice straw was either baled and removed before flooding (n = 55 surveys) or nothing was done to the rice straw after harvest (n = 3 surveys), when compared to all other post-harvest treatment methods. Elphick and Oring (1998) observed higher shorebird densities within rice fields where straw had been incorporated into the soil. Small shorebirds feed primarily on invertebrates, and incorporation of rice straw into the soil may increase invertebrate populations (Lawler and Dritz 2005). Consequently, post-harvest treatment of rice fields that removes the residual rice straw or prevents the rice straw from becoming incorporated into the soil may decrease use of rice fields by shorebirds. Overall, our data suggest that post-harvest treatments of rice fields that result in emergent dirt clods within rice checks, or the removal of rice straw from rice fields before flooding, might decrease overall bird use of winter-flooded rice fields.

Hunting Intensity

We found that the rice fields where hunting did not occur were used by greater numbers of dabbling ducks and supported a higher diversity of species than rice fields that had been hunted ≥ 3 days week^{-1} (Figure 6). Dabbling ducks may change their behavior and habitat use when hunting activity is high and spend more time in sanctuaries during daylight hours (McDuie et al. 2021). Additionally, the greatest number of species were observed in rice fields when there was no hunting within the rice field at any point during the winter, and in rice fields where there was hunting elsewhere within the same rice property but not within the surveyed rice field (Figure A4). In contrast, we did not detect an effect of hunting intensity on the use of winter-flooded rice fields by shorebirds, wading birds, or geese. We note that our study was designed to avoid surveying rice checks on any days when hunting was occurring within the rice field, so these results should be interpreted as residual effects of hunting presence on other days.

Management Implications

Bird use of flooded rice fields was influenced by several habitat variables that could be managed by landowners and prioritized through landowner incentive programs, depending on the overall objectives for the managed habitat. Water depth had the greatest impact on bird use of flooded rice fields, although peak abundance for all birds, dabbling ducks, shorebirds, wading birds, and geese occurred at different depths, indicating that managing for the ideal water depth of rice fields will depend on which group of birds is being targeted. If the management objective is to provide habitat for the greatest overall number of birds, then incentive programs that prioritized rice fields that maintain water depths of approximately 21 cm may be most successful, although that management strategy would primarily support waterfowl and decrease use by shorebirds and wading birds. Additionally, prioritizing rice fields for incentive programs that can flood early—when fewer alternative flooded habitats are available in the Central Valley—could increase bird use of rice fields enrolled in the program. Incentive programs might benefit from implementing a strategy of staggering the flooding of rice fields—especially early in the fall—to maintain a portion of fields throughout the season that have been flooded <30 days and >100 days, both of which had substantially higher overall bird densities. If

https://doi.org/10.15447/sfews.2024v22iss3art3

the management objective is to provide habitat for the greatest number of wading birds and shorebirds, then maintaining some rice fields, or rice checks, with water depths < 13 cm may increase abundance. Further, if the management objective is to support the highest bird diversity, incentive programs may be most successful if they can work with landowners to maintain a diversity of habitats within or among rice checks and rice fields. Specifically, bird diversity might benefit from rice fields that contain a mosaic of microhabitats, including variation in water depths and emergent vegetation heights and the availability of mudflat habitat within rice fields. Land managers might be able to be achieve landscape-level habitat diversity by managing rice checks within the same rice field differently or by varying management decisions among rice fields at a larger spatial scale.

Flooded rice fields provide critical habitat for many waterfowl and waterbird species in California's Central Valley, especially during drought conditions when there is less alternative wetland habitat available than during normal water years (Petrie et al. 2016; Reiter et al. 2018). During the late January 2023 midwinter waterfowl survey, 2.67 million dabbling ducks were counted in the Sacramento and Yolo–Delta Central Valley Joint Venture Planning Regions where we conducted our study (Brady and Weaver 2023). The midwinter waterfowl survey was not conducted in 2022, so we calculated the mean of the five most recent midwinter surveys (2016, 2017, 2018, 2020, and 2023; Brady and Weaver 2023) and used this value as an estimate of the wintering waterfowl during January 2022 (4.17 million dabbling ducks; Skalos and Weaver 2018; Brady and Weaver 2023). The CVJV estimates that winter-flooded rice provides 73% of the wintering habitat for ducks in the Sacramento and Yolo–Delta Planning Regions (CVJV 2020); under this assumption, winter-flooded rice fields could provide midwinter habitat for 3.05 (2012–2022) and 1.95 (2022–2023) million dabbling ducks. Using our average dabbling duck densities predicted for winter-flooded rice fields at the same time of year as the 2023 midwinter waterfowl survey (January 21; 92 days after the start of flooding), we estimated that the 16,248 ha (2021–2022) and 8,448 ha (2022–2023) of rice fields enrolled in the California Winter Rice Habitat Incentive Program provided habitat for 644,888 dabbling ducks per day in 2021-2022 (density of 39.7 dabbling ducks per ha) and 163,020 dabbling ducks per day in 2022–2023 (density of 19.3 dabbling ducks per ha). Based on our predictions, the properties enrolled in the incentive program may have been used by 21.2% (2021–2022) and 8.4% (2022–2023) of the dabbling ducks expected to use winter-flooded rice habitat in the Sacramento and Yolo-Delta Planning Regions. Winter-flooded rice fields enrolled in the landowner incentive program represented 10.5% of the 155,400 ha and 8.2% of the 102,792 ha of rice planted in the prior spring in these regions (USDA National Agricultural Statistics Service c2015–2024). Generally, 64% of planted rice fields are flooded in the winter (CVJV 2020), which means that the landowner incentive program likely represented closer to 16.5% (2021–2022) and 12.9% (2022–2023) of the total winter-flooded rice habitat. The bird densities we observed in the winter of 2021–2022 may have been higher than prior studies because of extreme drought conditions that limited wetland habitats and the overall extent of flooded rice, thereby concentrating birds within the landowner incentive program lands. Nevertheless, rice fields enrolled in the California Winter Rice Habitat Incentive Program likely represented a substantial portion of both the winter-flooded rice fields and the population of wintering ducks in the Central Valley of California.

ACKNOWLEDGMENTS

This study was funded by the California Department of Fish and Wildlife's California Winter Rice Habitat Incentive Program and the US Geological Survey's Ecosystems Mission Area. We thank the California Department of Fish and Wildlife's Wetland Conservation Program and B. Olson, K. Navarre, J. Kohl, A. Greenawalt, and L. Matthews for logistical and project support; B. Cooney, B. Fettig, and M. Toney for assistance with the field surveys; R. Klinger for assistance with the design of statistical analyses; E. Matchett, C. Elphick, and N. Warnock for providing comments that improved the manuscript; and numerous private landowners and managers for their participation in field surveys. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the US Government.

REFERENCES

Ackerman JT, Hartman CA, Eagles–Smith CA, Herzog MP, Davis JA, Ichikawa G, Bonnema A. 2015. Estimating mercury exposure of piscivorous birds and sport fish using prey fish monitoring. Environ Sci Technol. [accessed 2018 Sep 21];49:13596–13604. *https://doi.org/10.1021/acs.est.5b02691*

Ackerman JT, Herzog MP, Yarris GS, Casazza ML, Burns EW, Eadie JM. 2014. Waterfowl ecology and management. In: Moyle PB, Manfree A, Fiedler PL, editors. Suisun Marsh: ecological history and possible futures. Berkeley (CA): University of California Press. p. 103–132.

Ackerman JT, Takekawa JY, Orthmeyer DL, Fleskes JP, Yee JL, Kruse KL. 2006. Spatial use by wintering greater white-fronted geese relative to a decade of habitat change in California's Central Valley. J Wildl Manag. [accessed 2013 June 26];70:965–976. *https://doi.org/10.2193/0022-541X(2006)70[965:SUBWGW]2.0.CO;2*

Arnold TW. 2010. Uninformative parameters and model selection using Akaike's information criterion. J Wildl Manag. [accessed 2013 May 20];74:1175–1178. *https://doi.org/10.2193/2009-367*

Bates D, Mächler M, Bolker B, Walker S. 2015. Fitting linear mixed-effects models using lme4. J Stat Softw. [accessed 2018 Sep 21];67:1–48. *https://doi.org/10.18637/jss.v067.i01*

Bird JA, Pettygrove GS, Eadie JM. 2000. The impact of waterfowl foraging on the decomposition of rice straw: mutual benefits for rice growers and waterfowl. J Appl Ecol. [accessed 2023 Jun 30];37:728–741. *https://doi.org/10.1046/j.1365-2664.2000.00539.x*

Brady, C, Weaver M. 2023. Central Valley Midwinter Waterfowl Survey 2023 Results. Sacramento (CA): California Department of Fish and Wildlife Waterfowl Program. Final report. 12 p.

Brasher MG, Giocomo JJ, Azure DA, Bartuszevige AM, Flaspohler ME, Harrigal DE, Olson BW, Pitre JM, Renner RW, Stephens SE, et al. 2019. The history and importance of private lands for North American waterfowl conservation. Wildl Soc Bull. [accessed 2022 Nov 21];43:338–354. *https://doi.org/10.1002/wsb.1002*

Brooks ME, Kristensen K, van Benthem KJ, Magnusson A, Berg CW, Nielsen A, Skaug HJ, Maechler M, Bolker BM. 2017. glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. R J. [accessed 2023 Oct 11];9:378–400. *https://doi.org/10.32614/RJ-2017-066*

Burnham KP, Anderson DR. 2002. Model selection and multimodel inference: a practical information-theoretic approach. (2nd ed.) New York (NY): Springer–Verlag. 488 p.

[CVJV] Central Valley Joint Venture. 2020. Central Valley Joint Venture 2020 Implementation Plan. Sacramento (CA): US Fish and Wildlife Service. [accessed 2020 July 7];243 p. Available from: *http://www.centralvalleyjointventure.org/science/2020-implementation-plan*

Dahl TE. 1990. Wetland losses in the United States: 1780s to 1980s. Washington (DC): US Department of the Interior, Fish and Wildlife Service, [accessed 2022 Jul 26]. 13 p. Available from: *https://www.fws.gov/sites/default/files/documents/Wetlands-Losses-in-the-United-States-1780s-to-1980s.pdf*

Day JH, Colwell MA. 1998. Waterbird communities in rice fields subjected to different post-harvest treatments. Colon Waterbirds. [accessed 2018 Sep 21];21:185. *https://doi.org/10.2307/1521905*

Donnelly JP, Moore JN, Casazza ML, Coons SP. 2022. Functional wetland loss drives emerging risks to waterbird migration networks. Front Ecol Evol. [accessed 2022 Jul 26];10:1–18. *https://doi.org/10.3389/fevo.2022.844278*

Dybala KE, Reiter ME, Hickey CM, Shuford WD, Strum KM, Yarris GS. 2017. A bioenergetics approach to setting conservation objectives for non-breeding shorebirds in California's Central Valley. San Franc Estuary Watershed Sci. [accessed 2018 Sep 21];15(1). *https://doi.org/10.15447/sfews.2017v15iss1art2*

Elphick CS. 2000. Functional equivalency between rice fields and seminatural wetland habitats. Conserv Biol. [accessed 2018 Sep 21];14:181–191. *https://www.jstor.org/stable/2641917*

Elphick CS, Oring LW. 1998. Winter management of Californian rice fields for waterbirds. J Appl Ecol. [accessed 2018 Sep 21];35:95–108. *https://doi.org/10.1046/j.1365-2664.1998.00274.x*

Elphick CS, Oring LW. 2003. Conservation implications of flooding rice fields on winter waterbird communities. Agric Ecosyst Environ. [accessed 2018 Sep 21];94:17–29. *https://doi.org/10.1016/S0167-8809(02)00022-1*

Fasola M, Ruiz X. 1996. The value of rice fields as substitutes for natural wetlands for waterbirds in the Mediterranean region. Waterbirds. [accessed 2023 Dec 8];19:122–128. *https://www.jstor.org/stable/1521955*

Fleskes JP, Casazza ML, Overton CT, Matchett EL, Yee JL. 2018. Changes in the abundance and distribution of waterfowl wintering in the Central Valley of California, 1973–2000. In: Shuford WD, Gill Jr RE, Handel CM, editors. Trends and traditions: avifaunal change in western North America. (Studies of western birds 3.) Camarillo (CA): Western Field Ornithologists. [accessed 2023 Dec 8];50–74. *https://doi.org/10.21199/swb3.2*

Fleskes JP, Halstead BJ, Casazza ML, Coates PS, Kohl JD, Skalos DA. 2012. Waste rice seed in conventional and stripper-head harvested fields in California: implications for wintering waterfowl. J Fish Wildl Manag. [accessed 2018 Sep 21];3:266–275. *https://doi.org/10.3996/022012-JFWM-014*

Fleskes JP, Yee JL, Casazza ML, Miller MR, Takekawa JY, Orthmeyer DL. 2005. Waterfowl distribution, movements, and habitat use relative to recent habitat changes in the Central Valley of California: a cooperative project to investigate impacts of the Central Valley Habitat Joint Venture and changing agricultural practices on the ecology of wintering waterfowl. Final report. Dixon (CA): US Geological Survey-Western Ecological Research Center, Dixon Field Station. [accessed 2018 Sep 21]. 190 p. Available from: *https://pubs.usgs.gov/publication/96876*

Garr JD. 2014. The status of rice fields during midwinter in the Sacramento Valley, California. Colusa (CA). Central Valley Habitat Joint Venture, The California Rice Commission, and Ducks Unlimited. Final report 2014. 7 p.

Gilmer DS, Miller MR, Bauer RD, Ledonne JR. 1982. California's Central Valley wintering waterfowl: concerns and challenges. Washington (DC): Transactions of the Forty-Seventh North American Wildlife and Natural Resources Conference. p. 441–452.

Greer DM, Dugger BD, Reinecke KJ, Petrie MJ. 2009. Depletion of rice as food of waterfowl wintering in the Mississippi Alluvial Valley. J Wildl Manag. [accessed 2023 Jun 30];73:1125–1133. *https://doi.org/10.2193/2008-250*

Heitmeyer ME, Connelly DP, Pederson RL. 1989. The Central, Imperial, and Coachella valleys of California. In: Smith LM, Pederson RL, Kaminski RM, editors. Habitat management for migrating and wintering waterfowl in North America. Lubbock (TX): Texas Tech Press. p. 475–505.

Hill MO. 1973. Diversity and evenness: a unifying notation and its consequences. Ecology. [accessed 2023 Nov 14];54:427–432. *https://doi.org/10.2307/1934352*

Krapu GL. 1979. Nutrition of female dabbling ducks during reproduction. In: Bookhout EA, editor. Waterfowl and wetlands–an integrated review. Proceedings of the 39th annual symposium of the North-Central section the Midwest Fish and Wildlife Conference; 1977 Dec 5; Madison. Bethesda (MD): The Wildlife Society. p. 59–70.

Lawler SP, Dritz DA. 2005. Straw and winter flooding benefit mosquitoes and other insects in a rice agroecosystem. Ecol Appl. [accessed 2023 Jun 1];15:2052–2059. *https://doi.org/10.1890/03-5420*

Lourenço PM, Mandema FS, Hooijmeijer JCEW, Granadeiro JP, Piersma T. 2010. Site selection and resource depletion in black-tailed godwits *Limosa l. limosa* eating rice during northward migration. J Anim Ecol. [accessed 2023 Jun 30];79:522–528. *https://doi.org/10.1111/j.1365-2656.2009.01654.x*

MacDonald ZG, Nielsen SE, Acorn JH. 2017. Negative relationships between species richness and evenness render common diversity indices inadequate for assessing long-term trends in butterfly diversity. Biodivers Conserv. [accessed 2023 Oct 24];26:617–629. https://doi.org/10.1007/s10531-016-1261-0

Manley SW, Kaminski RM, Reinecke KJ, Gerard PD. 2004. Waterbird foods in winter-managed ricefields in Mississippi. J Wildl Manag. [accessed 2023 Jun 1];68:74–83. https://doi.org/10.2193/0022-541x(2004)068[0074:wfiwri]2.0.co;2

Matthews L. 2019. Changing post-harvest practices, impacts on waste grain availability and grower's perspectives: a study of rice and corn fields for wintering waterfowl in the Central Valley. [master's thesis]. [Davis (CA)]: University of California–Davis. 95 p.

McDuie F, Lorenz AA, Klinger RC, Overton CT, Feldheim CL, Ackerman JT, Casazza ML. 2021. Informing wetland management with waterfowl movement and sanctuary use responses to human-induced disturbance. J Environ Manage. [accessed 2023 Jun 30];297:113170. https://doi.org/10.1016/j.jenvman.2021.113170

McGarigal K. 2014. Fragstats: a spatial pattern analysis program for categorical maps. Help. [accessed 2018 Sep 14]. Available from: https://fragstats.org/index.php.

Miller MR. 1987. Fall and winter foods of northern pintails in the Sacramento Valley, California. J Wildl Manage. [accessed 2023 Sep 11];51:405–414. https://doi.org/10.2307/3801027

Miller MR, Garr JD, Coates PS. 2010. Changes in the status of harvested rice fields in the Sacramento Valley, California: implications for wintering waterfowl. Wetlands. [accessed 2010 Oct 11];30:939–947. https://doi.org/10.1007/s13157-010-0090-2

Naylor LW. 2002. Evaluating moist-soil seed production and management in Central Valley wetlands to determine habitat needs for waterfowl. [master's thesis]. [Davis (CA)]: University of California–Davis. 80 p.

Oksanen J, Blanchet FG, Friendly M, Kindt R, Legendre P, McGlinn D, Minchin PR, O'Hara RB, Simpson GL, Solymos P, Stevens MHH, Wagner H. 2017. Vegan: Community Ecology Package. The R Project for Statistical Computing. [accessed 2022 Dec 19]. Available from: https://cran.r-project.org/web/packages/vegan/index.html

Peterson SH, Ackerman JT. 2024. Bird use of winter-flooded rice fields in the Sacramento Valley, California. US Geological Survey data release. [accessed 2024 Sep 1]. Available from: https://doi.org/10.5066/P9S48E60.

Petrie MJ, Fleskes JP, Wolder MA, Isola CR, Yarris GS, Skalos DA. 2016. Potential effects of drought on carrying capacity for wintering waterfowl in the Central Valley of California. J Fish Wildl Manag. [accessed 2018 Sep 24];7:1–15. https://doi.org/10.3996/082015-JFWM-082

R Core Team. 2022. R: a language and environment for statistical computing. Vienna (Austria): R Foundation for Statistical Computing. Available from: https://www.R-project.org/

Reiter ME, Elliott NK, Jongsomjit D, Golet GH, Reynolds MD. 2018. Impact of extreme drought and incentive programs on flooded agriculture and wetlands in California's Central Valley. Peer J. [accessed 2020 Dec 1];2018:1–22. https://doi.org/10.7717/peerj.5147

Sesser KA, Iglecia M, Reiter ME, Strum KM, Hickey M, Kelsey R, Skalos DA. 2018. Waterbird response to variable-timing of drawdown in rice fields after winter-flooding. PLoS ONE [accessed 2018 Nov 13];(13)10:e0204800. https://doi.org/10.1371/journal.pone.0204800

Sesser KA, Reiter ME, Skalos DA, Strum KM, Hickey CM. 2016. Waterbird response to management practices in rice fields intended to reduce greenhouse gas emissions. Biol Conserv. [accessed 2018 Nov 13];(197:69–79. https://doi.org/10.1016/j.biocon.2016.02.021

Shuford WD, Dybala KE. 2017. Conservation objectives for wintering and breeding waterbirds in California's Central Valley. San Franc Estuary Watershed Sci. [accessed 2018 Sep 24];15(1). https://doi.org/10.15447/sfews.2017v15iss1art4

Shuford WD, Page GW, Kjelmyr JE. 1998. Patterns and dynamics of shorebird use of California's Central Valley. Condor. [accessed 2018 Sep 24];100:227–244. *https://doi.org/10.2307/1370264*

Shuford WD, Reiter ME, Sesser KA, Hickey CM, Golet GH. 2019. The relative importance of agricultural and wetland habitats to waterbirds in the Sacramento–San Joaquin River Delta of California. San Franc Estuary Watershed Sci. [accessed 2023 Sep 27];17(1). *https://doi.org/10.15447/sfews.2019v17iss1art2*

Skalos D, Weaver M. 2018. Central Valley Midwinter Waterfowl Survey Redesign. Final update. Sacramento (CA): California Department of Fish and Wildlife Waterfowl Program. Final report. [accessed 2023 Nov 13]. 44 p. Available from: *https://lab.data.ca.gov/dataset/wintering-waterfowl-monitoring-central-valley-1955-2022*

Skalos D, Weaver M. 2020. Central Valley Midwinter Waterfowl Survey 2020 Results. Sacramento (CA): California Department of Fish and Wildlife Waterfowl Program. [accessed 2023 Nov 13]. Final report. 10 p. Available from: *https://lab.data.ca.gov/dataset/wintering-waterfowl-monitoring-central-valley-1955-2022*

Stafford JD, Kaminski RM, Reinecke KJ. 2010. Avian foods, foraging and habitat conservation in world rice fields. Waterbirds. [accessed 2023 Dec 7];33:133–150. *https://doi.org/10.1675/063.033.s110*

Stenzel LE, Page GW. 2018. Trends in abundance of wintering waterbirds relative to rainfall patterns at a central California estuary, 1972–2015. In: Shuford WD, Gill Jr RE, Handel CM, editors. Trends and traditions: avifaunal change in western North America. Studies of western birds 3. Camarillo (CA): Western Field Ornithologists. p. 236–257. *https://doi.org/10.21199/swb3.13*

Strum KM, Reiter ME, Hartman CA, Iglecia MN, Kelsey TR, Hickey CM. 2013. Winter management of California's rice fields to maximize waterbird habitat and minimize water use. Agric Ecosyst Environ. [accessed 2013 Oct21];179:116–124. *https://doi.org/10.1016/j.agee.2013.08.003*

Swanson GA, Meyer MI, Adomaitis VA. 1985. Foods consumed by breeding mallards on wetlands of south-central North Dakota. J Wildl Manag [accessed 2023 Dec 27];49(1):197–203. *https://www.jstor.org/stable/3801871*

Tidwell PR, Webb EB, Vrtiska MP, Bishop AA. 2013. Diets and food selection of female mallards and blue-winged teal during spring migration. J Fish Wildl Manag. [accessed 2023 Dec 7];4:63–74. *https://doi.org/10.3996/072012-JFWM-062*

USDA National Agricultural Statistics Service. c2015–2024. Quick Stats [database]. [accessed 2024 Mar 12]. Available from: *https://quickstats.nass.usda.gov*

Warnock N, Page GW, Stenzel LE. 1995. Non-migratory movements of Dunlins on their California wintering grounds. Wilson Bull. [accessed 2024 Mar 3];107:131–139. *https://www.jstor.org/stable/4163518*

Wilen BO, Frayer WE. 1990. Status and trends of US wetlands and deepwater habitats. For Ecol Manage. [accessed 2021 Nov 5];33–34:181–192. *https://doi.org/10.1016/0378-1127(90)90192-E*