Synergies between agricultural production and shorebird conservation with climate change in the Central Valley, California, with optimized water allocation and multi-benefit land use

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Abstract

Conservation planning that enhances the resiliency of biodiversity to climate change requires adaptive water and land use decision-making in the most cost-efficient way. This has many challenges since the landscapes with high biodiversity can embrace intense human production activities, particularly agriculture. Conventionally, water and land used for conservation are often regarded as tradeoffs to agricultural productivity. This study, however, found that agricultural water and land use could synergize with shorebird conservation in the Central Valley, California. If informed decisions are made to guide strategic land use, landscapes can adapt to climate change and offer multiple benefits, for example, managed wetlands and the right timing of crops can mitigate flood risk and protect the shorebird population. This study used a coupled economic optimization model with a species distribution model, using remote-sensing and citizen science data. The objective is to assess the impacts of agricultural water and land use decisions under different climate change scenarios on 10 shorebird species populations in California's Central Valley. Our results showed that strategic water and land management can offer favorable habitats to targeted shorebirds with a land composition that is composed of diversified crop categories complementary to wetlands. This study demonstrates that agricultural lands can be as important as wetlands to shorebirds to sustain their migratory stages across the year, if strategically managed. Wetland restoration without species habitat preference information can lead to population shrinkage since wetland types vary in habitat importance to shorebird species studied in this research. Business as usual land use and climate change will decrease shorebirds' breeding season and population to the same degree as how they impact non-breeding populations. Therefore, conservation efforts should be put towards the whole annual migration circle instead of only the non-breeding season. The synergies between agricultural production and shorebird conservation were found in the scenarios that favor agricultural production water use but also favor habitat provisioning to shorebirds in Central Valley, California.

1. Introduction

Accelerated global biodiversity loss (Butchart et al., 2010) is calling for immediate conservation action. Conservation decisions need to be informed by the best available data and science to face the fundamental challenge of rapid global environmental change. Mathematical modeling can support these efforts by recommending strategies that can mitigate the consequences of both anthropogenic causes of biodiversity loss, such as changes in water flows and land use, and natural causes, such as extreme hydrological events and climate shifts.

Many decades of progress have been made in studying avian biodiversity (Tobias et al., 2020). Avian biodiversity plays a major role in studying the origin, distribution, and function of biological diversity, as birds are mobile and responsive to land use and climate change. They shift their migratory patterns with landscape changes (Linssen et al., 2023). Birds' habitats are, therefore, usually sharply aligned with eco-zones or boundaries of different land cover classes (Grinnell, 1917). Detailed information on bird distribution, annual circle movements, and species-habitat association provide an opportunity for monitoring and assessing the impacts of land use and climate change on a broad scale of biodiversity changes (Tobias et al., 2022).

California's Central Valley, a vast agricultural region that occupies a central position in California, is an example of a highly modified landscape. Water and land use for agricultural production have largely altered wildlife habitat. The channelization and fragmentation of land for pursuing agricultural production plus stable urban water use have distorted the ecosystem and habitat provisioning, resulting in a loss of nearly 90% of California's original wetland habitat over the last century (Burke, 1966). The 10% maintained wetlands are mostly disconnected from natural water sources and are, therefore, managed wetlands flooded by surface water diversion and groundwater pumping identical to irrigated agricultural water supplies. The rising cost of water (Singh & Lund, 2015), along with the shortage and budgetary constraints on environmental water use, is deemed to be a major impediment to meeting the water supply needs of wetlands to provide habitats for wildlife.

The Central Valley is the most important region for migrating and wintering shorebirds of the Pacific Flyway in North America (USGS, 2020; Reynolds et al., 2018), with both managed wetlands and flooded agriculture as important habitats for shorebird populations (Reiter, et al., 2015). Migratory shorebirds belong to a globally declining sub-group of species. They are wide-ranging yet they have unmet habitat needs in the Central Valley area (Reynolds et al., 2018). Under climate change, the temporal and spatial surface water demand and supply discrepancies have been exacerbated, laying pressure on groundwater pumping (Herman et al., 2018). To control groundwater overdraft, California's Sustainable Groundwater Management Act (SGMA) requires local water users to bring groundwater use to sustainable levels by the early 2040s. This is expected to bring some of Central Valley's farmland out of production permanently or temporarily (B. Bryant et al., 2023; Hanak et al., 2023) , which would cause additional habitat loss for birds that rely on croplands such as rice, corn, pasture, and alfalfa for energy and habitat (Hanak et al., 2019). Thus, questions concerning how land and water use change compound the impacts of climate change on avian biodiversity should be solved at a fine spatial scale and be adaptive to the full annual migratory circle. Better, management of water and land can not only address these groundwater and land-scape changes, but could also restore and re-create birds' habitat at the right location and timing (California Landscape Conservation Cooperative, 2018).

There has been more extensive research on birds' habitat adjacent to the Sacramento Valley and Sacramento-San Joaquin Valley Delta (Reiter, et al., 2015), and less research in the southern half of the Central Valley, known as the San Joaquin Valley. However, shorebirds are prevalent across the whole Central Valley. These two regions have some key differences, for example, the Sacramento Valley has abundant surface water resources for habitat use. However, the Sacramento Valley and the San Joaquin Valley are highly connected via a complex network of water conveyance and allocation systems. Though previous research has thoroughly studied wetland habitat in the region (Reiter et al., 2015; Wilson et al., 2022), there are gaps in understanding climate change and land use change impacts on birds' habitat in Central Valley. Shorebirds rely on a mosaic of flooded areas and open fields, with habitat importance varying seasonally (Shuford et al., 2019). To establish a comprehensive picture of birds' conservation ecology, the intercorrelation between bird abundance and each land cover class is required beyond wetland areas and types of analysis (Reiter, et al., 2015). Although Shuford et al., 2019 showed habitat relative importance to birds, this research expanded and included the full-year annual circle variations in habitat importance.

Research applied to avian biodiversity and identifying bird habitats on farmlands are abundant (Estrada-Carmona et al., 2022). The Central Valley, California, produces half the nation's fruit and vegetables (USDA/FSA, 2011); hereby, its agricultural economy is of critical importance for food security and for local disadvantaged communities' income (Fernandez-Bou et al., 2021). Hou et al.,2022 studied species range and abundance, but there is a lack of a comprehensive and applicable land use analysis that incorporates the complexities of land use dynamics in Central Valley. Thus, as defined by the reconciliation ecology (Rosenzweig, 2003) framework, management decisions can create an economically efficient agroecosystem, enabling prosperous biodiversity on populous landscapes like the Central Valley, that maximize synergies between conservation and agricultural economy.

Previous studies have linked agricultural economics with bird systematic conservation planning (B. P. Bryant et al., 2020) or avian biodiversity conservation optimization (Wesemeyer et al., 2023), providing meaningful implications for using economic optimization in minimizing tradeoffs. However, these studies didn't explicitly reveal how change in each crop category positively or negatively affects each species' population. In addition, we also need the rarely achieved bird abundance data projected for climate and land use change, which are great resources for effective conservation planning (Johnston et al., 2015). This research advances the understanding of integrating human decisions into projections of shorebirds' population changes with spatial-explicit land use and land cover change scenarios under climate change (Figure 1).

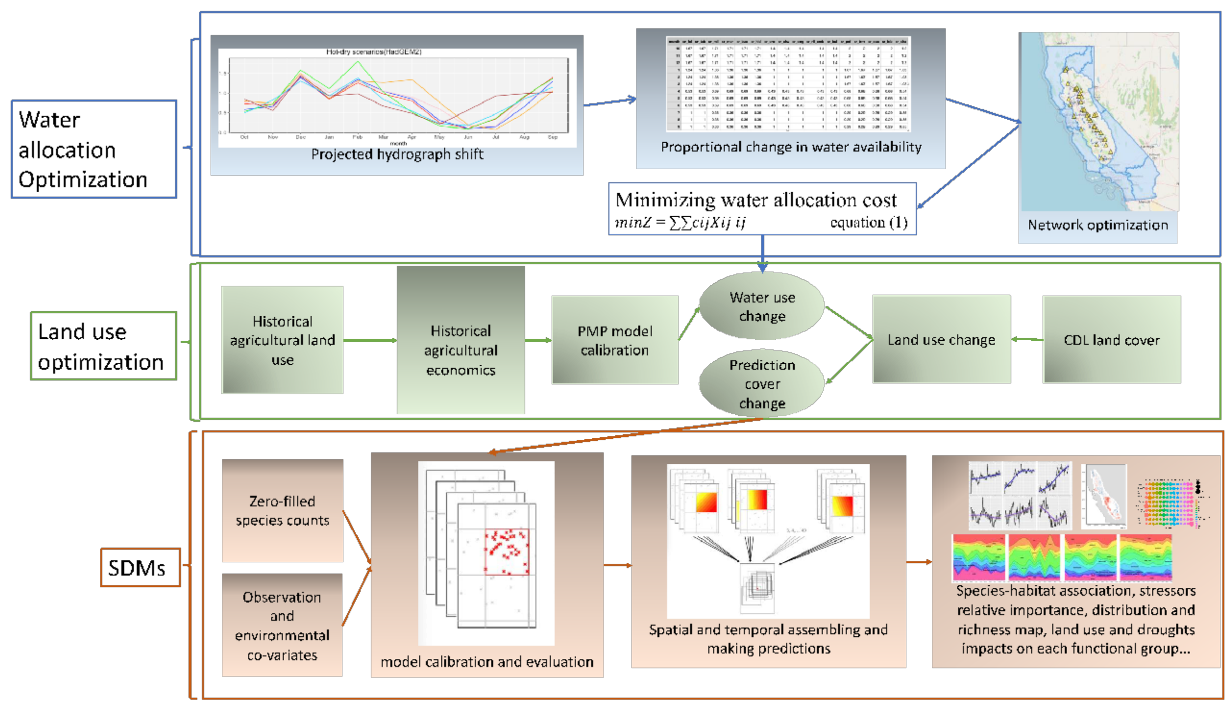

Figure 1 Integrated decision support framework assisting agricultural water and land use management for conservation co-benefit

For this study, we used spatial and temporal explicit ensembled species distribution models (SDM) (Fink et al., 2010a) coupled with water and land use economic optimization models to model 10 shorebirds' population change with land use and climate change. We identified the hotspot of population change spatially and seasonal variations in population across different combined climate and land use scenarios in the Central Valley, California. We applied the change factors from land use optimization models (Howitt et al., 2012) to the remote sensing information to capture the agricultural land use change with climate change and characterize the landscape and habitat information spatially. This is possible with the application of remote-sensing information that not only makes economic optimization spatially explicit but also makes prediction surface at a scale, which improves the predictive performance of other modeling efforts applied in this area, such as SDMs that use only typo-climatic variables (Schwager & Berg, 2021; Deneu et al., 2022; Pinto-Ledezma & Cavender-Bares, 2021) and not socioeconomic cropland dynamics. We conducted this analysis for 10 shorebirds species, assessing their relative abundance change with potential land use changes and climate change scenarios. With this study, we aim to inform the compatible management of agricultural lands for habitat provisioning and prioritize environmental water use at the right time and location.

2. Methods

2.1 Water allocations with climate change

Under climate change, local seasonal hydrologic signature shifts with hydroclimatic alternation will impact agricultural production and affect year-by-year growing decisions. The objective of the proposed model is to generate optimized water allocation under the ever-changing hydroclimate conditions with and without environmental deliveries for habitat and groundwater overdraft constraints. We use a state-wide network optimization for water allocation, CALVIN (https://calvin.ucdavis.edu/calvin-project-overview) (Draper et al., 2003), which is used to minimize water allocation costs to the environment, agriculture, and urban users based on historical or climate change hydrology. Modeled water allocation decisions are also affected by water management regulations, which for this study are conservation requirements to control long-term groundwater overdrafts and increase environmental water use to meet refuge delivery requirements to restore and sustain wetland ecosystems (CVPIA, 1937).

Table 1 Combined climate change and management scenarios

Scenario names	Scenario description	Environmental water use	Climate condition	Groundwater overdraft
Historical	Historical business-as-usual	Historical	Historical	Overdraft
DREAM	California Dreamin'	Increased for non-dry years	Warm-wet (MIROC5)	No-overdraft
BBAU	Bad Business-As-Usual	Historical	Warm-wet (MIROC5)	Overdraft
EEM	Everyone Equally Miserable	Increased for non-dry years	Hot-dry (HadGEM2)	No-overdraft
DUST	Central Valley Dustbowl	Historical	Hot-dry (HadGEM2)	Overdraft

Five combined climate and management scenarios used in this research (Table 1), developed by Li et al., 2024, include warm-wet climate with/without conservation requirements (with DREAM; without: BBAU), hot-dry climate with/without conservation requirements (with EEM; without DUST), and historical scenarios without conservation requirements. In scenarios with conservation requirements, environmental water use was only increased for wet and normal years, not the dry years.

2.2 Agricultural land use optimization

We used an economic optimization model, the Positive Mathematical Programming (PMP) model (Howitt, 1995), of irrigated agriculture throughout California's Central Valley to assess the proportional changes in the growing area of each crop type based on the water availabilities in different scenarios generated from water use optimization.

The economic model uses historical agricultural use of input (i.e., land and water), crop yields, costs, and revenues in its calibration. Following Howitt et al. (2012), the calibrated non-linear optimization model optimizes agricultural economic incomes by allocating land and water to crops. This modeling approach has shown multiple applications (Heckelei et al., 2012) and accurately represented the dynamics of agricultural production and changes to water availability (Cortignani & Severini, 2009), climate change (Withey & Cornelis Van Kooten, 2011), and water management (Shirzadi Laskookalayeh et al., 2022). For the calibration of the model, we used the observed agricultural land use acquired from the publicly available LandIQ 2018 survey (Kimmelshue, 2017), historical crop prices and yields from the USDA National Agricultural Statistics Service (USDA NASS) program, and crop production costs such as labor, supplies, and land costs from the Archived Cost and Return Studies of UC Davis (https://coststudies.ucdavis.edu/en/archived/). We also used water balance information to calculate crop water use, Evapotranspiration (ET), Effective Precipitation (EP), Applied Water (AW), and Evapotranspiration of Applied Water (ETAW) (the amount of irrigation water applied) from the CADWR (2024)

The PMP model calibration process catches the non-linearity in the interrelations between realized agricultural land allocation, cultivation resources use, and gross revenues. The calibrated model optimizes agricultural production based on the assumption that growing decisions by farmers in the real world reflect a series of considerations of expertise and the overhead costs of land, infrastructure, and equipment, which restrict the behavior of purely "profit-driven" decisions. Thus, high-profit crops are not always favored in optimizing profit.

The agricultural land is optimized to produce growing areas of each crop type in each groundwater basin within a range of possible scenarios of incremental changes in applied water. The realized change in applied water in the PMP model was acquired from the water allocation optimization described in the previous section. Average land use change and land use change by water year types between historical and climate change scenarios were associated with agricultural water use average change and changes by water year types, respectively, acquired from the water optimization outputs.

2.3. Spatial and temporal species distribution models

We used the spatial and temporal ensemble species distribution models (Fink et al., 2010b) that were broadly used in literature (Fink et al., 2020; Johnston et al., 2015, 2021; Schuster et al., 2019) for abundance modeling. We set all stixels' temporal width to 30 days. The spatial dimensions were sized to 5° longitude and 5° latitude. The STEM ensemble consisted of 100 randomly located and oriented grids of overlapping spatiotemporal stixels generated in this way. Additional information about the specification of the ensemble design was provided by Johnston et al. 2015 (Johnston et al., 2015). The ensemble estimates of relative abundance were calculated by averaging across all the base model estimates for a given location and date. We generated ensemble estimates for 3km x 3km resolution, year-round, weekly relative abundance for population mapping, and seasonal trend estimates average across the 10-year timeframe under all climate change and land use scenarios. We first trained the model with 10-year training data and predicted relative abundance for every single day and average across the week. We repeated the same prediction for the same week of each of the 10 years and acquired the average weekly relative abundance. Such average weekly relative abundance was predicted for all 52 weeks of a year for each 3 x 3 km grid cell across the Central Valley for each shorebird species.

2.4. Boosted regression trees sub-models

Models of citizen science data often require large numbers of observation co-variates and environmental predictors, which restricts the use of parametric statistical techniques.(Hochachka et al., 2011). Non-parametric model techniques are applicable to embedded multiple co-variates such as the Generalized Addictive Model (Matutini et al., 2021) or the Random Forest model (Robinson et al., 2018). We used a gradient-boosted regression tree for abundance modeling in R GBM packages (Ridgeway & Developers G, 2024), specifying 1000 trees, 0.95 bag fraction, and up to 2-way interactions. Gradient boosting of regression trees (BRT) produces highly robust, interpretable procedures for both regression and classification (Friedman, 2001). Tree models allow for viewing the partial dependence of bird abundance on selected small subsets of the input predictors (land use types). Partial dependance is the marginal effect of a given predictor on relative abundance averaged across the other predictors. To calculate partial dependance, relative abundance was first predicted at each value within a regular sequence from 0 to 1 (fractional cover) of a focal predictor for a random subsample of the training, but all other predictors were left as is. The resulting relative abundance predictions are then averaged across all the checklists in the training dataset, giving an estimate of the relative abundance at a specific value of the focal predictor (Johnston et al., 2021). The tree models can also estimate relative importance of land cover predictors, implicating habitats' importance to bird population distributions and trends. The relative importance of a predictor is calculated as the corresponding empirical improvement in squared error as a result of the split with this predictor as the splitting variable at a node, averaged over all of the boosted trees (Friedman, 2001).

To assess the quality of the ensembled BRT abundance estimates, we validated the model by Spearman's rank correlation (SRC), the Average Absolute Deviation (AAD), the Percentage of Outlier (Predicted count is 10 times bigger than the observed count), and the Pseudo R-Squared. We tested the predictions first with at 3 km × 3 km × 1 week resolution for seasonal variation performance among species using weekly sliced training data. Evaluations were performed separately for each week of the year to control for seasonal variation in the occurrence and abundance of the species population. Then, we tested the stability of the model performance across species with 3 km × 3 km × 10-year resolution. We used 25 Monte Carlo randomized splits of 80% train, 20% test from the filtered checklists of all years for each species and evaluated all four predictive performance statistics, assuming the randomized splits will control for the even spatial and temporal distribution of the train and test.

2.5. Remote-sensed predictor variables

All models of abundance used the same suite of covariates (i.e., predictor variables). Referring to Fink et al., 2020, we chose observation effort covariates of the observation start time, the day of the year (1–366) and the year when the search was conducted, the duration spent searching for birds, whether the observer was stationary or traveling, the distance traveled during the search, and the number of people in the observation group. These covariates both capture the hourly, seasonal, or intra- and interannual variation in detectability of species and presence and describe the observation process. Each checklist is also linked to a set of coordinates of longitude and latitude as spatial covariates.

There were two layers of environmental descriptors as environmental covariates: one layer is the typographic information and elevation describing the foundation of the landscape, and another layer is the land use land cover classifying the landscape. Topographic variables of northness and eastness (combination of orientation and slope) and elevation were acquired at 1km resolution from (Amatulli et al., 2018), a database for a suite of global topographic data based on an enhanced global elevation model named the GMTED2010 (Danielson & Gesch, 2011). The landcover data for this project is Cropland Data Layer (CDL) over a 10-year period (2010–2020) acquired from the CropScape (USDA, 2022) (created annually using moderate resolution satellite imagery and extensive agricultural ground truth). We merged 131 crop types included in CDL into seven crop categories and named them in alignment with the agricultural land use change output from the economic model as described below. Crop categories used in this research were categorized considering their potential to benefit birds. The other_crops category includes field/row crops, vegetables, and a few fruits (the crosswalk table of these two is in Supplementary Information Table 1). Landcover is summarized as fractional cover, the proportional landcover of each class within a modeling unit (3km x 3km). We applied the agricultural percentage change acquired from the agricultural land use optimization model (at the groundwater basin level) to each land cover class for each 3km × 3km square. We didn't include climatic variables as climatic variation is embedded in the land covers generated from different hydroclimatic and management scenarios. Further land cover processing to reflect land use land cover changes under climate change was described in the Prediction Surface section.

To obtain a complete picture of projected land cover classes for semi-permanent and seasonal wetland changes under a combination of all four climate and land use change scenarios, we incorporated the results of the LUCAS land use model by Wilson et al. 2022 (Wilson et al., 2022). The expansion rate in urban areas was set to be a consistent 20%, which was relatively conservative compared to the LUCAS projections (Wilson et al., 2022). Climate change scenarios are dummy years and months between Dec 1st, 2050, and Nov 30th, 2060, matched to land cover modified from historical land cover between Dec 1st, 2010, and Nov 30th, 2020.

Habitat vertical structure determines the availability of food sources and filters species by their locomotion, two factors that can strongly influence species occurrence and abundance. Combining horizontal and vertical habitat structure predictors creates the most powerful prediction models (Culbert et al., 2013). We included the canopy top height variable as a predictor. Canopy height was acquired from a derived product of the Global Ecosystem Dynamics Investigation (GEDI) L1B waveforms in Lang et al. (2022).

We calculated the relative importance and partial dependence of all predictors for each species to analyze the species-habitat association. Despite the favorable features of remote sensing information, such as high spatial and temporal resolution, quasi-global coverage, and range of data products (e.g., land cover, precipitation, plant productivity, biophysical variables), their application as biodiversity models' predictors still awaits validation and extension (Pinto-Ledezma & Cavender-Bares, 2021). All the environmental predictors used in the SDMs are remote-sensing derived products in this research.

2.6.Shorebirds' observation data and processing

We attained the species count data between Dec 2010 and Nov 2020 from eBird (Sullivan, et al., 2009), an online citizen science bird-monitoring project (Fink et al., 2010a). Shorebird species were picked from protected wetland sites in Central Valley (CVJV, 2020b; Duffy et al., 2011) (occurs over 75%). The bird species selected (Table 2) are the species for which the Central Valley population is of primary importance (i.e., populations are likely to be larger in the Central Valley than in other shorebird planning regions in the United States (Hickey et al., 2003)) Conservation status designations vary based on the U.S. Shorebird Conservation Plan (USCPP, 2015). The non-breeding months are from November to February with some species extending into March. Pre-breeding migrations of all species are usually from February to June. Table 2 shows the shorebirds' morphological information and habitat. Birds' morphology indicates suitable habitats because beak size indicates the species' diet and wing size indicates the locomotion features (Tobias et al., 2022).

Table 2 Shorebird morphological information and habitat studied in this paper

Species	Conservation categories	Body mass (g)	Beak length /width (mm)	Wing length (mm)	Habitat	Non-breeding/breeding seasons	Ebird Checklists count
American Avocet *(Recurvirostra americana)*	Watch-list (Long-term Planning and Responsibility)	304	73.9 /6.6	218.2	Shallow lakes, impoundments, protected coastal water	20 Dec-25 Jan/10 May -21 Jun	83589
Long-Billed Curlew *(Numenius americanus)*	Watch-list (Management Attention)	583	141.5 /7.6	266.8	Pastures, mudflats, beaches	22 Nov- 8 Feb/17 May -14 Jun	83415
Least Sandpiper *(Calidris minutilla)*	Least Concern	22.9	15.1 /2.4	85.2	Muddy grass and marshes, inland wetlands	13 Dec-8 Mar/14 Jun -21 Jun	85192
Dunlin *(Calidris alpina)*	Watch-list (Management Attention)	51.9	28.1 /3.2	114.5	Mudflats, beaches in large flocks	Dec 13-Feb 15/ 14 Jun-5 Jul	83042
Mountain Plover *(Charadrius montanus)*	Watch-list (Immediate Management Action)	95.7	17 /3.9	146.2	Huge, plowed field in winter, prairies in summer, in large flocks	16 Nov- 8 Mar/ 10 May-6 Jul	81189
Lesser Yellowlegs *(Tringa flavipes)*	Watch-list (Management Attention)	77.5	30.6 /3.0	151.2	Flooded fields, shallow ponds	22 Nov-1 Feb/7 Jun-14Jun	82448
Greater Yellowlegs *(Tringa melanoleuca)*	Least Concern	161.7	45.9 /4.8	194.5	Flooded fields, marshes	28 Dec-8 Feb/7 Jun-14 Jun	88494
Black-necked Stilt *(Himantopus mexicanus)*	ESA listed	176.8	51 /4.5	217.5	Shallow wetlands, flood plains, rice fields and other flooded agricultural fields	29 Nov-1 Mar/31 May-5Jul	85888
Killdeer *(Charadrius vociferus)*	Common Shorebirds in Decline	96.4	13.1 /3.5	158.8	Pastures, plowed fields, large lawns, even at a great distance from water	20 Dec-25 Jan/10 May-25Jun	96629
Long-billed Dowitcher *(Limnodromus scolopaceus)*	Least Concern	104.4	61.9 /4.5	145.5	Lakes, ponds, marshes, flooded fields	27 Dec-1 Feb/ 14 Jun-21 Jun	84475

Beak Length-length from the anterior edge of the nostrils to the tip of the beak

Beak Width – width of the beak at the anterior edge of the nostrils
Wing Length –from the carpal joint to the tip of the longest primary on the unflatten wing
ESA listed-A shorebird population that is listed under the U.S. Endangered Species Act (ESA)

Therefore, we provided the morphology information from AVONET (Tobias et al., 2022) (supplementary data of BridTree (Pigot et al., 2020)) for further species-habitat relation analysis. Some species are considered of least concern by ICUN, yet they can still be vulnerable to habitat loss (ABC, 2024). Species habitat preference information was from Karlson 2014 (Karlson, 2014) and Ebird (Sullivan et al., 2009).

We studied 10 years of bird distributions, taking the average weekly abundance for each of the 52 weeks of the annual migration cycle. This is to minimize the impacts of interannual variation of observation and increase accuracy of seasonal variation estimation of shorebirds' abundance. We set the land cover time series back by one month, considering bird population change may lag in timing compared to the land cover change. The number of Ebird Checklists indicates the number of checklists for training and testing models after filtering and spatial subsampling. Checklists used for analysis were from observation periods between Dec 1st, 2010, and Nov 30th, 2020 in Central Valley, California, with data collected using either the "stationary count" or "traveling count" protocol. We used only "complete checklists," which were defined by the participants as a complete record of all the species they detected and were able to identify. Afterward, we zero-filled the data to create presence/absence abundance from the filtered complete presence-only checklists. For all counts, data were only used from checklists with start times falling between 5 am and 8 pm (i.e., likely daylight hours), and the total search times of ≤5 hours; additionally, for traveling counts, transect distances were limited to ≤5 km, and with 10 or fewer observers. We withheld a random 20% of the resultant data set for each species for model validation.

We performed subsampling of the eBird data prior to modeling following the method used by (Johnston et al., 2021). Specifically, we created a hexagonal grid with 5 km between cells across the Central Valley and separately subsampled randomly one detection and one non-detection in each of the hexagons per week to manage the spatial-temporal bias (some seasons and locations are more accessible to citizen scientists than others) (Khan & Verma, 2022). As a result, subsampling *decreased* the overall number of checklists and increased detections. Since there are more non-detections than detections for most species in the citizen science data, we also managed to control underestimates in model predictions through subsampling. The resulting filtered checklist number for each species is listed in Table 2. The checklist data between Dec 1st, 2010, and Nov 30th, 2020, were linked to CDL data for the same period in the historical scenario and to the predicted land use land cover for the period of from Dec 1st, 2050, to Nov 30th, 2060.

3. Results

3.1. **Agricultural water use and land use change**

Climate change and conservation requirements that control groundwater overdraft and prioritize environmental water use will decrease agricultural water use availability across all future combined scenarios compared to historical scenarios in all water year types. In figure 2, the Sacramento Valley saw the biggest reduction in agricultural water use for the dry years of DUST scenarios (hot-dry without conservation requirements). Conserving groundwater will compensate for the reduction of agricultural water by almost 6% (see EEM scenario). In the normal and wet years of the Sacramento Valley, because of the increasing environmental water use requirements, agricultural water use decreased further by 1-5% than in climate change-only scenarios.

In the San Joaquin Valley, long-term groundwater overdraft control requirements decreased agricultural water use by 4% more than climate change (DREAM compared to BBAU). In almost all scenarios except DUST, the San Joaquin Valley saw a greater reduction in agricultural water use in wet years than in normal years. Conservation requirements impact agricultural water use in the San Joaquin Valley more than in the Sacramento Valley, as it decreased agricultural water use by 8% more than climate change-only scenarios, no matter hot-dry or warm-wet climates.

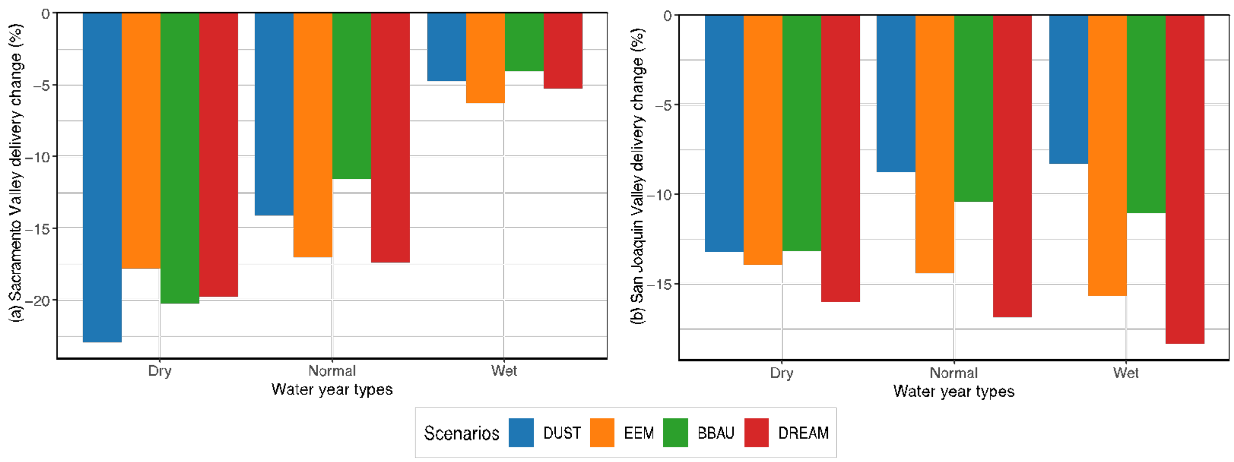

Figure 2. Agricultural water delivery change in combined future climate change and management scenarios by water year types

The shortages in agricultural water deliveries will limit agricultural production. New extremes in hydrological events under hydroclimatic conditions, plus water management decisions, will affect farming decisions. Overall, rice-growing areas are the most volatile ones with climate change (Figure 2).

All crop categories will decrease in growing areas, yet perennial crops are the most resilient. Rice had the biggest reduction in the future dry years, and pasture had the biggest reduction in percentage in normal and wet years. Most violins in Figure 3 have two peaks because of the contrast between warm-wet and hot-dry conditions. If conservation requirements significantly impact growing areas, more than 3 peaks were shown, such as the rice violin in the dry year scenario (Figure 3). That is we will see less growing area reduction in rice if we prioritize wetland restoration. Grain crops were more impacted under climate change combined scenarios than alfalfa, corn, or field and row crops. Climatic uncertainties affected cropping patterns more than conservation requirements.

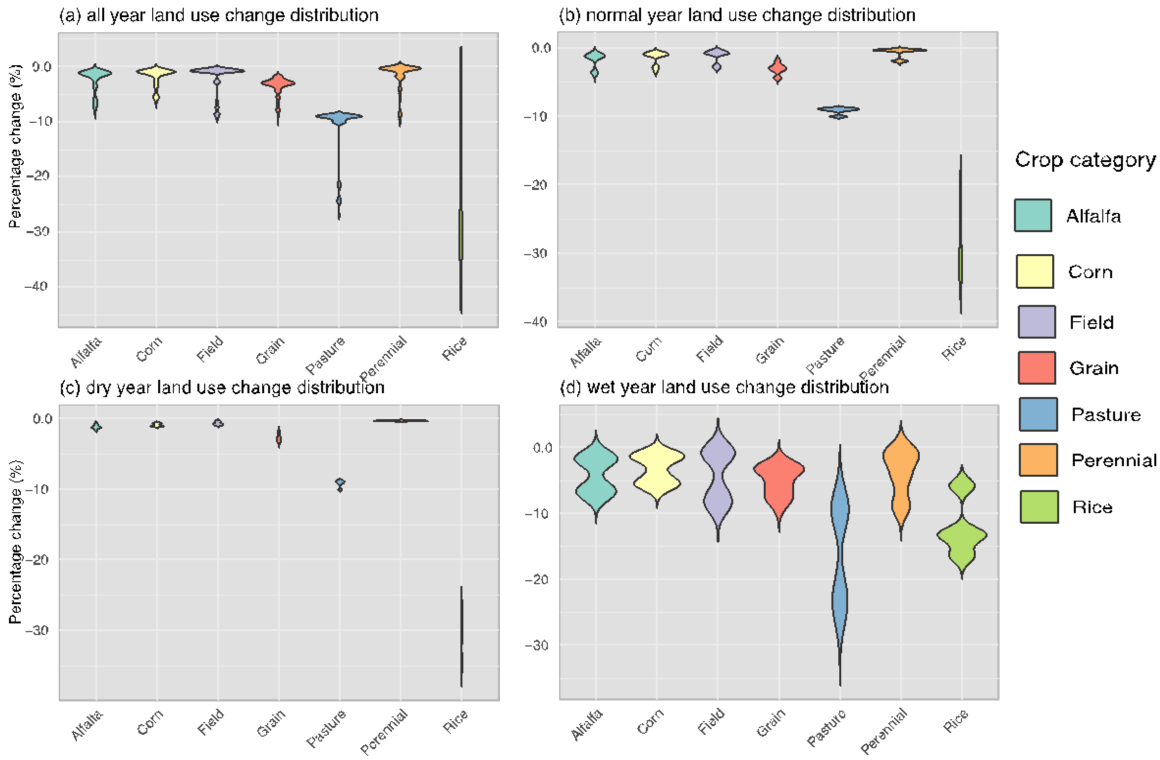

Figure 3 Distribution of agricultural land use percentage changes across different combined climate and management scenarios within (a) all water year types, (b) normal year, (c) dry year, and (d) wet year. (The width of each curve corresponds with the approximate frequency of percentage change in change interval)

3.2.Shorebirds' species-habitat association

Partial dependence of bird abundance on selected small subsets of the input predictors can inform us about species' habitat preferences (Figure 4). Hereby, we can learn how land use change affects birds' populations to assist in biodiversity monitoring and conservation. At community level, we all know intuitively that wetlands are rich in biodiversity and that wetlands restoration and re-creation would support wildlife. However, land-use changes take place in a progressive manner, allowing species to adapt wherever possible. Returning habitat or land cover to a pristine condition may not be wise or cost-effective for targeted species, as showcased here.

Figure 4 shows the partial dependence of species relative abundance on wetlands, water cover, and rice cover in Central Valley, California. The preference for wetlands by species is more consistent for semi-permanent wetlands. The abundance of birds increases when fractional semi-wetland cover (proportion of a land cover class in one grid cell) increases, with Mountain Plover as the only exception. Seasonal wetlands are only favorable to black-necked stilt from the point of population growth with increasing fractional cover. Half of the species, namely dunlin, greater yellowlegs, killdeer, least-sandpiper, and mountain plover, reflect? the trend of decreasing and increasing population with increasing fractional cover. This trend means when seasonal wetlands are too small, they may not have enough connectivity for nutrition inputs and, therefore, do not matter significantly to birds. However, once the seasonal wetlands reach a certain size, they start to attract birds with sufficient invertebrates or other sources of the birds' food.

The trend curve flipped for species of American Avocet, Lesser Yellowlegs, Long-billed Curlew, and Long-billed Dowitcher. Populations increase with increasing fractions of seasonal wetlands and decrease at a point ranging from around 0.12 to 0.18. The reason behind this is that seasonal wetlands take big chunks of land, indicating the unsuitability for agriculture or other vegetation that cannot survive in deep water and, therefore, wetlands lack food sources and perch locations for birds. Thus, water depth may play a part in the determination of population change in aspects of food sources, water quality, and local climates. The fractions of water cover have the most rigid positive influence on bird population growth across multiple species among these three land cover classes.

The partial dependence on rice followed the same path as semi-permanent wetlands (Figure 4). Overall, there was a consistent positive association between rice cover percentage and population growth of shorebirds among different species. Greater Yellowlegs, long-billed Curlew, and Killdeer populations increase with these three crop categories. Based on what we know about these three shorebirds species' life history from observation and monitoring, they all prefer open fields and arable lands. Corn and pasture follow a similar pattern to seasonal wetlands.

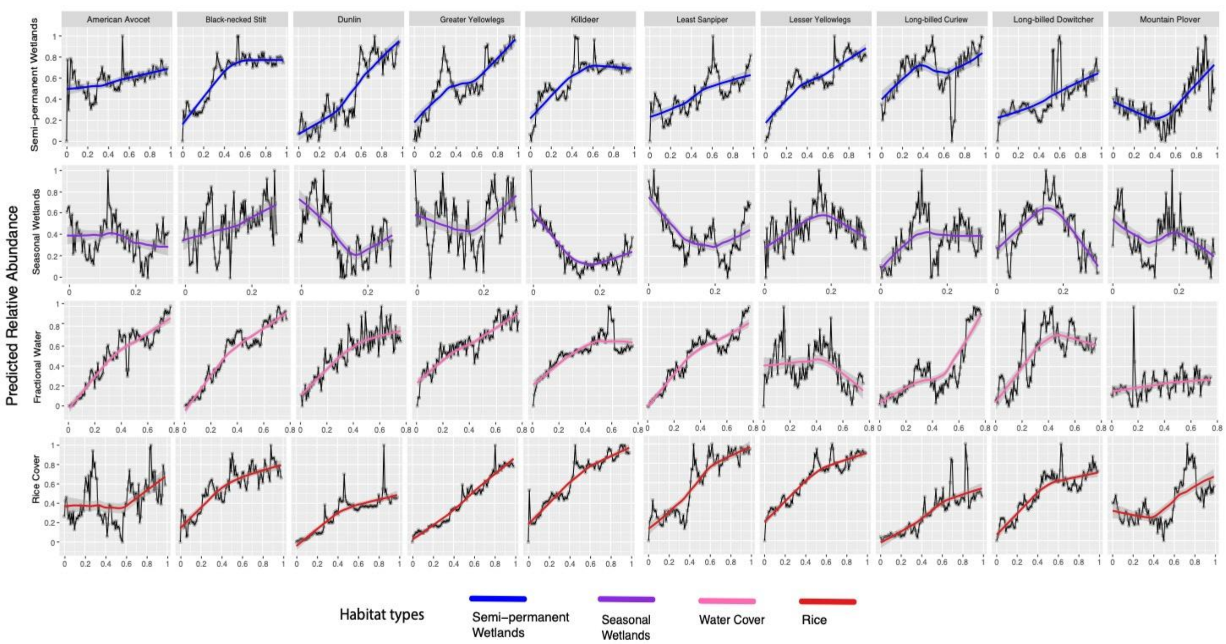

Figure 4. Partial dependence of 10 shorebird species relative abundance on wetlands, water, and rice cover in Central Valley, California.

Semi-permanent wetlands have a more consistent positive association with shorebirds' population growth than seasonal wetlands. When we zoomed in to look at seasonal wetlands, we found that for some species, seasonal wetlands need to reach a certain size to provide enough connectivity for nutrient inputs and water temperature and quality conditions. However, or the other species populations decline if the wetland areas become too large and start to show a lack of perches or preferred vegetation.

Policies that are favorable for wetland restoration but disadvantageous for agriculture can harm birds' population growth, indicating that the benefit of species and biodiversity conservation synergizes with the agricultural economy. However, the tipping points of negative impacts are much bigger than those of seasonal wetlands. We learned that shorebird species prefer to depend on a collage of diversified land covers. Secondly, we learned that arable lands and wetlands have equal impact on shorebirds' population change. Lastly, some predictors, such as water cover and rice, showed a smoother relationship with relative abundance than other predictors.

We considered interactions in the tree models between predictors that are not displayed in the partial dependence charts of dependent variable species counts by looking at the predictors' correlation matrix in Figure 5. When interpreting partial dependence, it is important to watch out for complex interaction effects beneath the direct association between the focal predictor and the predictive. Figure 4 showed that there were very light interactions between different sets of two predictors, except that each typographical variable's mean has a relatively strong correlation with its own standard deviation.

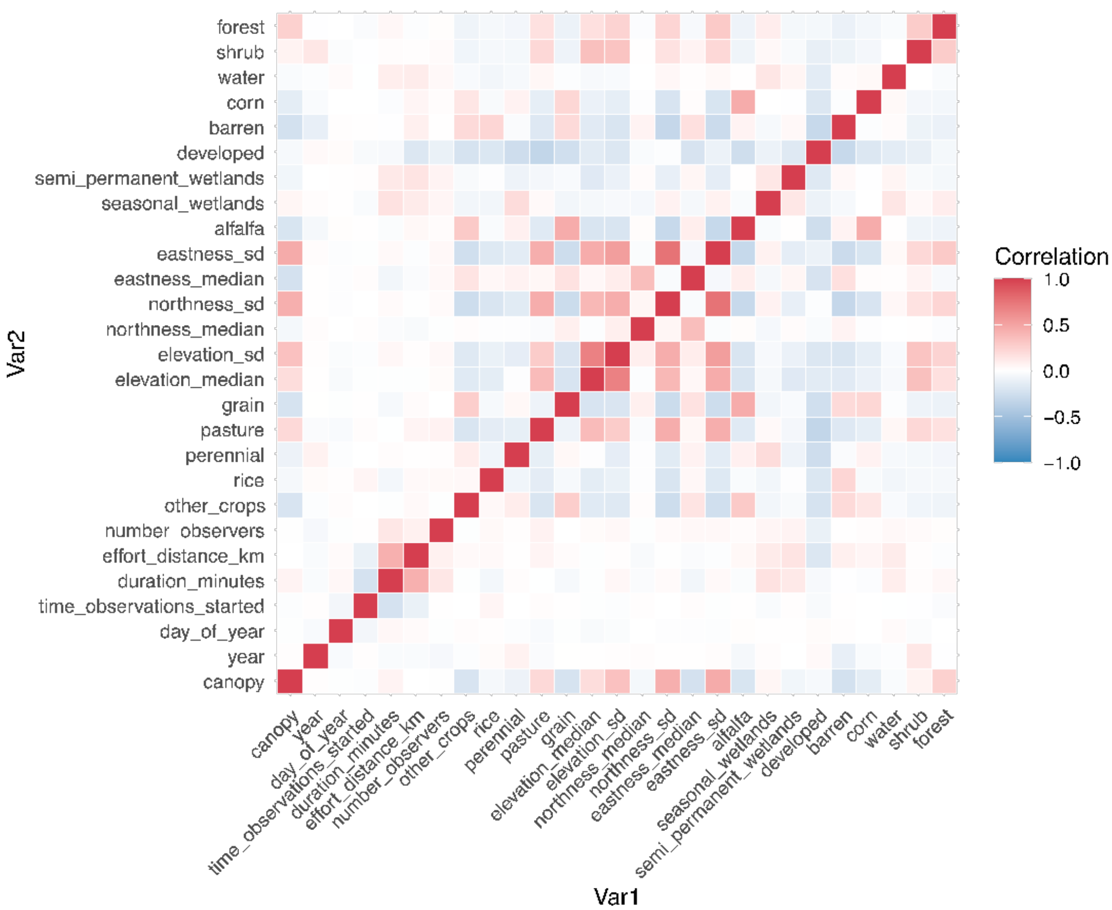

Figure 5 Predictors correlation matrix of the boosted regression tree models

This weak correlation among predictors made us more confident in explaining how land use change is affecting shorebirds' population directly. In addition, the correlation result validated the prediction surface as a meaningful representation of the real world. For example, the distance of observation efforts correlates positively with observation time spent. Shrub and forest cover show medium level (around 0.4) co-existence, both of which favor higher elevation in the Central Valley since lower flat lands are occupied mostly by agriculture. As a result, the canopy is higher in higher-elevation regions with more diversified landscape orientations and elevations. Urban areas are negatively correlated with all other land cover types, indicating that developed areas are negative to landscape variability and arable land areas but are slightly positive to the "year" variable for the reason of urban growth.

3.3.Shorebirds' habitat affinity

After examining the directional influence of different land cover classes, we moved next to evaluate the magnitude of habitat importance to each individual species in Central Valley, California. In Figure 6, we can see which predictor is most important to which species, and on each type of habitat which species have the highest relative abundance. Specifically, Dunlin, Killdeer, and Lesser Yellowlegs have higher relative abundance on rice fields.

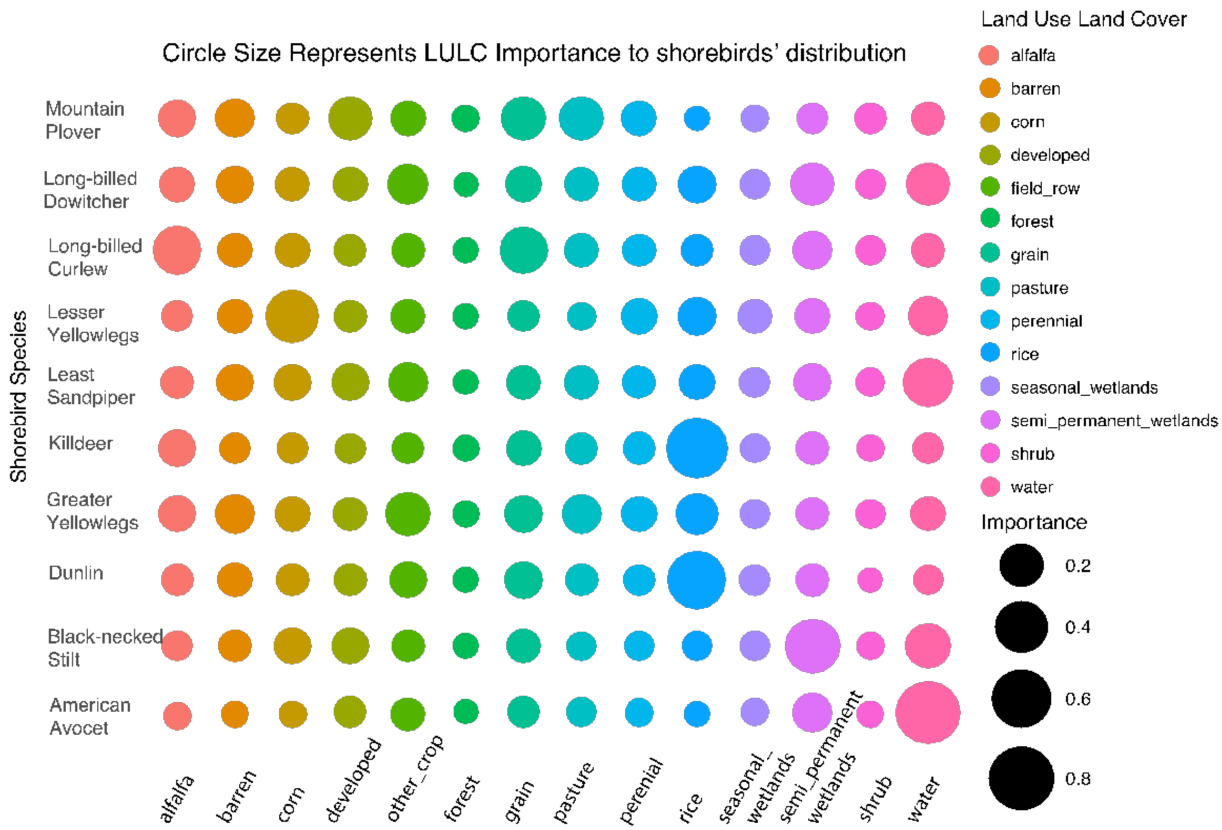

Figure 6 Predictor relative importance in the tree models to predict species' relative abundance distribution for 10 shorebird species in the Central Valley, California (circle color represents different land covers and circle size represents the predictor importance)

Although rice cover partial dependence showed similar graphs as water cover for different species, they have different importance when assigned to species level. To American Avocet, seconded by least sandpiper, water cover is disproportionately important for its abundance distribution prediction. Seasonal wetlands, forests, and shrubs have equally minor influence across different species and can potentially be removed from prediction if higher dimension prediction is less favorable for differently structured models than boosted regression tree models.

3.4.Shorebirds' abundance and range changes

The modeled shorebirds' counts – represented in relative abundance – were predicted weekly for each of the 52 weeks of each of the 10 years. Each of the 52 weeks' relative abundance was averaged across the 10 years to cancel the effects of uneven spatial and temporal observation and in interannual population variation to capture the seasonal variation. We then averaged the relative abundance of each 3km x 3km grid cell and across all weeks within a month to generate the seasonal shorebirds population change plot (shown in Figure 7). American Avocet, Black-necked Stilt, and Killdeer are prevalent year-round in the Central Valley. Therefore, their population increases after breeding seasons. For species that only stay in the Central Valley during non-breeding seasons and migrate elsewhere to breed, including Least Sandpiper, Long-billed Curlew or Long-billed Dowitcher, the annual circle patterns took a flying wings shape: both sides of the breeding season show higher populations than the breeding season.

Integrating all the seasonal patterns under all combined scenarios, we find that strategic land use change under climate change could make the Central Valley attractive to a bigger population of shorebirds. Almost all species have one or more climate change scenarios that are more favorable to their persistence based on the Central Valley landscape-level average abundance. Specifically, the DUST scenario in the green line saw increases in abundance of the American Avocet, Dunlin, Killdeer, and Less Yellowlegs across all seasons, with only two exceptions of Greater Yellowlegs and Least Sandpiper were only more abundant in the migratory season. For long-billed Curlew, the patterns under different scenarios are quite unique compared to other species, showing groundwater overdraft control and increasing wetland and environmental water use are favorable to the Long-billed Curlew population.

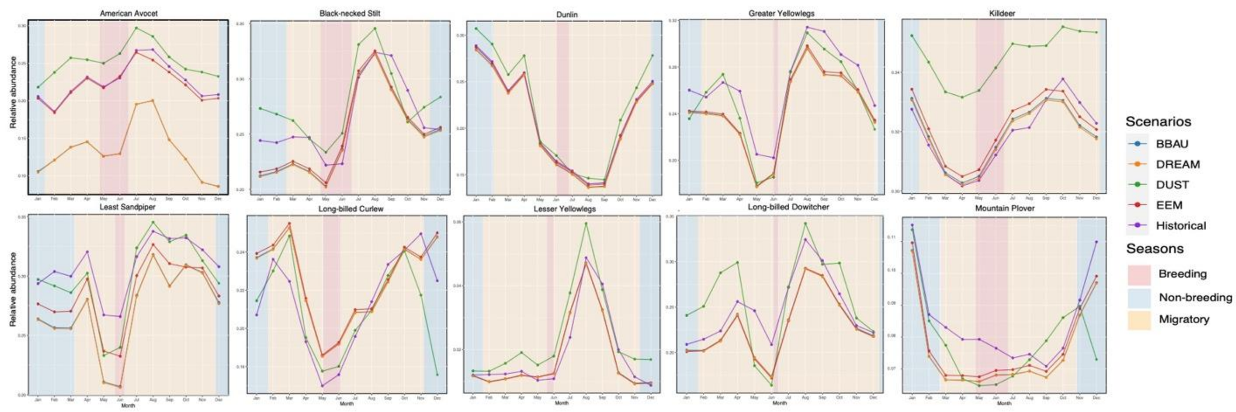

Figure 7 Shorebirds' population seasonal change under all combined climate and land use change scenarios (Historical: historical climate, historical water use, DUST: hot-dry condition, historical water use, EEM: hot-dry condition, sustainable groundwater use and increased environmental water use, BBAU: warm-wet condition, historical water use, EEM: warm-wet condition, sustainable groundwater use and increased environmental water use)

The least abundant scenario is the historical scenario without climate change effects between January and August. However, under climate change, the post-breeding migratory return of Long-billed Curlew is slower than the historical schedule. For the flying wing-shape seasonal pattern species, results show a dip of population density in the breeding season for half of the ten species, namely Greater yellowlegs, Killdeer, Least Sandpiper, Long-billed Curlew, and Mountain Plover under climate change. Although the grid level population density averaged across the landscape level can tell us about the seasonal variation from climate change impacts, we still like to be informed about the spatial distribution of these negative or positive changes for seasonal tipping points. Therefore, we presented shorebirds' population change maps under two combined scenarios in different annual migratory stages. Figure 8 shows such a group of maps for black-necked stilts.

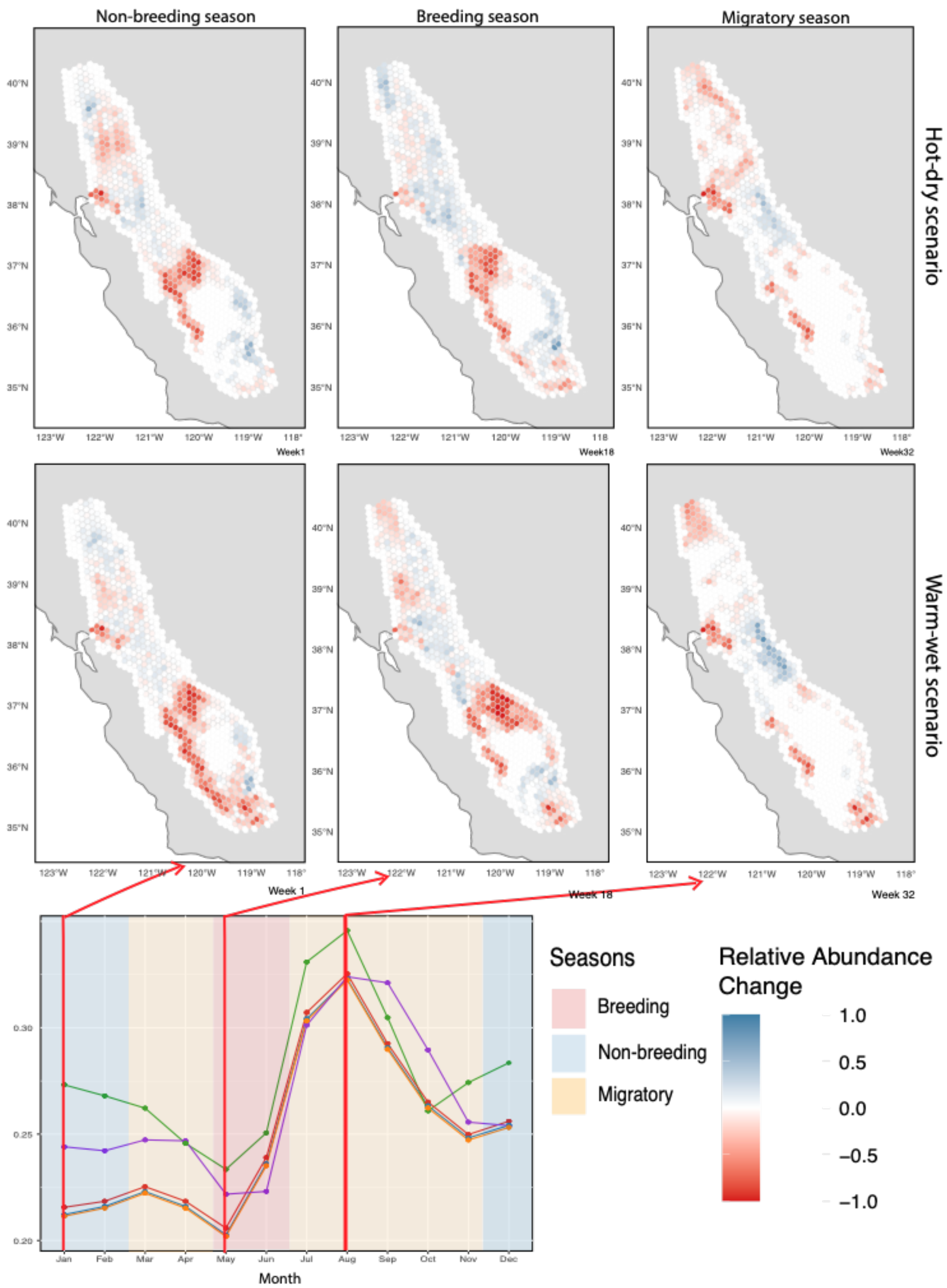

Figure 8 Black-necked Stilt relative abundance changes under two climate change scenarios (Hot-dry without conservation requirements and Warm-wet with conservation requirements) in three distinct migratory stages (Breeding, Non-breeding and Post-breeding Migratory)

From relative-abundance change maps of the Black-neck Stilt (Figure 7), we can tell the season with the most severe climate change impacts is the breeding season in both scenarios. Although in the hot-dry without conservation requirements scenario, the overall population increases with higher population density, the population distribution shifted north from the San Joaquin Valley to the Lower Sacramento Valley, likely because of the increased temperature caused by climate change. Under the hot-dry scenario, rice cover is significant, as we've seen in the land use change analysis. As a result, the prevalence of black-neck stilts was reduced during the non-breeding season in these rice fields. Another area that was impacted significantly across seasons and scenarios is the South Bay grasslands area, which was identified as a hotspot for potential habitat loss and bird population reduction under climate change.

In the warm-wet conditions combined with groundwater recharge and refugia delivery prioritization, Black-necked Stilts saw a big loss in population, particularly in non-breeding and breeding with conservation requirements scenarios. We think this loss resulted from the farmland to fallowing, which was originally the preferred food and habitat source. A certain land cover class, such as seasonal wetlands and marshes, may increase with conservation requirements. However, habitat preferences vary across species. For example, shorebirds like Black-neck Stilts prefer less vegetated lands; on the other hand, Greater Yellowlegs would choose their preferred vegetation for perching, such as shrubs, grasses, or small trees, including gale, dwarf birch, pine, and willow to perch. We invested in such species-specific habitat associations in the previous two sections.

3.5.Species Model validation

To quantify the quality of the abundance estimates, we computed Spearman's Rank Correlation (SRC), the Percentage of Predictive Outliers (PCT), the Mean Absolute Deviation (MAD), and the Pseudo R-squared. We first presented these statistics for the weekly prediction model to reflect seasonal variation in prediction performance (Figure 9). SRC measures how well the abundance estimates rank the observed abundances. This statistic has the least variation among species. All species have a positive association between estimated and observed abundances, centered around the magnitude range that is seen in Fink et al. 2020 (Fink et al., 2020). Breeding season ranking is slightly better than that of non-breeding season ranking, as shown in Figure 19 (a). Imperfect detection will decrease the maximum attainable values of the SRC. These weeks of the year during breeding season? are a most pleasant time for citizen scientists to go bird watching and collecting quality counts data, thereby leading to better data coverage and prediction performance in the sense of SRC.

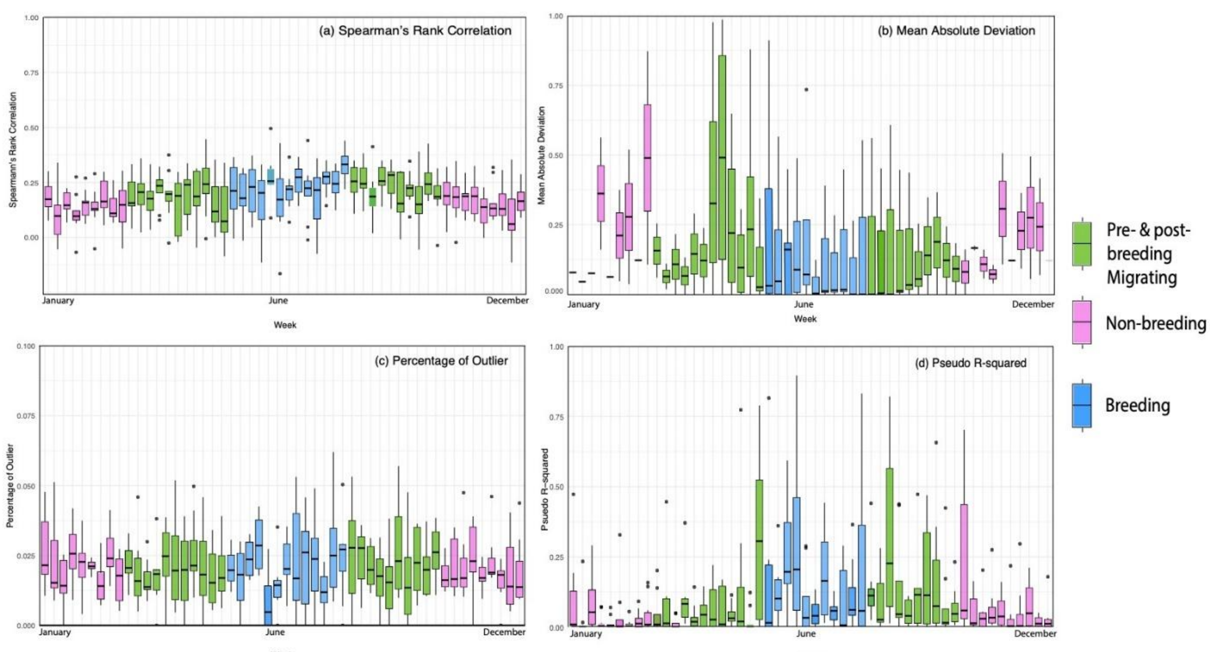

Figure 9 Model valuation statistics across different migratory seasons of all ten species population weekly prediction models (box color represents seasons, variation embedded in each box is the variation in statistics for different species prediction)

The MAD measures the average of the absolute deviations of the predicted counts from the observed counts. The pre-breeding migratory season saw the highest deviation and variation in predictive values. During these periods of the year, most species migrate to breeding locations; the occurrence rate, as a result, becomes so low that it affects abundance prediction performance stability. PCT measures the percentage of predictive values that are ten times or above the value of observed values. In the breeding and post-breeding seasons, when there are more likely to be high-value counts of shorebirds, there is a higher likelihood of predictive high values that are even extremely high at some checklist locations. Pseudo R-squared is a measure of goodness of fit of a model (indicator only), commonly used in models with large numbers of predators that are of non-linear interactions where traditional R-squared is not quite applicable. This statistic also showed very high variation across species in terms of model fit, explained by variation in species' detection likelihood and strength of predictors' power to explain species-level presence. Compared to other statistics, what is common is that during the favorable observation seasons, the model fit is better overall than the non-breeding season in the winter.

We subsequently used Monte Carlo randomized 80/20 splits of the checklists' data to test the stability in model performance for each of the ten species (Figure 10).

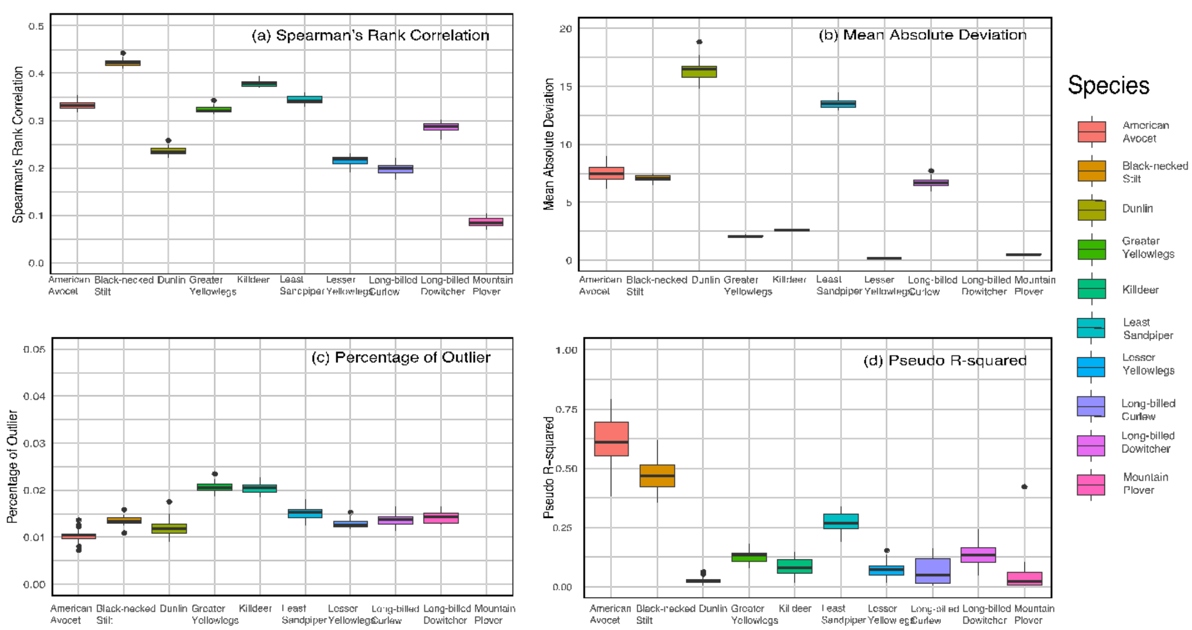

Figure 10 Model valuation statistics for all ten species across the whole 10-year analysis timeframe (box color represents species, and variation embedded in each box is the variation in statistics for different randomized splits of the selected checklists for training and testing).

The small values of the boxes' heights showed very concerted performance even when we randomly changed the training and test set of data within the selected checklists. Predictive values of American Avocet and Black-necked Stilt have closer ranked scores compared to observed values, which are also out of models of better goodness of fit compared to other species. Dunlin's prediction has the highest absolute deviation from observation. However, its PCT is very low compared to other species. The prevalence, occurrences in flocks, and popularity of Dunlin likely led to consistency in detection (fewer outliers) and a large number of observation attempts (higher deviation). The model performance is the poorest for Mountain Plovers, which is likely from data scarcity in some weeks of the year for this species. Overall, the validation statistics showed convincing model prediction powers to us from the aspects of model performance stability and how well the models reflect the seasonal variation in detections.

4. Discussion

Species abundance predictions are highly reliant on the observation data density and quality. Model trustworthiness is usually as good as data trustworthiness. First, we saw that a higher observation density of certain species facilitated better species distribution prediction performance. Besides using remote sensing data as environmental predictions, uncertainties in data quality that originated in methods used for retrieving topographical, biological, and ecological information from optical information are added. The vast research for ground-correction and terrain-correction would be able to manage the unrealistic above-ground biomass and canopy-top height quantification (Wang et al., 2019). Missions of Interferometric Synthetic-Aperture Radar increase elevation mapping resolution by increasing baselines of the waveform cycle (Wu et al., 2021). These improvements in optical data processing should reduce the uncertainty in future species distribution modeling work.

Climatic uncertainties have more impact on agricultural water and land use than water management decisions, such as whether to control groundwater overdrafts or increase environmental water use. Our scenarios with conservation requirements, however, are optimized for water conservation and wetland restoration and don't represent the best conservation practice for conserving birds. As we showed in the results, rice has a favorable habitat association with most of the studied avian species, aligning with other studies. Under climate change and changing water management decisions, rice declined in growing areas. A synergized approach for agriculture and conservation co-benefit would consider the benefits of rice as providing habitat to birds and fish.

Previous research found that ecosystem restoration back to tidal march on some occasions is harmful to birds' populations (Shuford et al., 2019). Therefore, it is important to maintain structured agriculture land use (a combination of different crop categories) across the landscape for supporting shorebirds in Central Valley, California. Based on our results, the different types of wetlands influence the viable population density and agriculture and wetlands combined will be most effective for sustainable a higher density of avian population. A similar conclusion was also found by Shuford et al., 2019.

5. Conclusion

Our results show that with land use and climate change, shorebird populations were impacted not only in the non-breeding season but also in the breeding season, indicated by the deep dip in seasonal population change curves. Future research and policy can be targeted to support landscapes for the non-breeding season of shorebirds. Conservation in Central Valley, California, may neglect the need to provide sufficient support for breeding shorebirds. We also identified the hotspots for land use and climate change impacts, such as the South Bay and San Joaquin Valley. Under climate change, shorebird populations are likely to shift east and north from the South Bay and San Joaquin Valley to the Lower Sacramento Valley as a result of increasing temperature or cropping pattern shifts.

We also found the synergy between the agricultural economy and shorebirds' conservation. Most species prefer habitats that are composed of diversified land use land covers with an optimized size scale of each land cover class. The loss in growing areas in some crop categories can cause direct shrinkage in shorebird population size. Rice is still the most favorable habitat, as conventionally regarded, particularly in the non-breeding season. However, in the agricultural land use under the water management and climate condition constraints, the resulting land use from the hot-dry climate under climate change may not necessarily embrace fewer shorebird populations than in warm and less-dry conditions with increased environmental flows and refuge deliveries. Our species-habitat association analysis revealed the reason, which showed that not all wetland types are more favorable to shorebird species than agricultural lands.

In conclusion, we found potential adaptive strategies to climate change that benefit shorebirds' population without reducing necessary agricultural water use and agricultural income. Decisions on diverting water for re-creation of habitat for targeted species should be fully informed by species' habitat preferences spatially and seasonally. Wetland restoration lacking such information may otherwise result in population loss due to insufficient connectivity and energy provision. If planned strategically with a diversified combination of crop categories, agricultural land use can increase the efficiency of providing habitat ecosystem service co-benefits. Our research assessed the land use and climate change impacts on 10 shorebird species' populations and revealed the impact mechanism by species-habitat association analysis in direction, magnitude, and across time. The results we provided will be useful in decision-making regarding conservation resource allocation at the right location and timing.

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